Master's Thesis

Thin-slicing process of preference in EEG

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Thin-slicing process of preference in EEG

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Abstract

"Social skills" are one of the research fields for behavioral and neuronal aspects. However, mechanisms of social skills are still unknown and thin-slicing is one of them. Thin-slicing defines an ability to find patterns based on a narrow slice of experience. Among them, the preference, which shows significant results in a previous study, is the sufficient topic for studying temporal sequence because the preference can divide the acquisition of others' information and the prediction of their preference. In behavioral aspects, mechanism of the preference can consider the aspects of others and one-self. When a person predicts the preference of others, she/he first considers their own liking and then estimates the other's preference using perceived difference between the others and oneself. In neural aspects, medial prefrontal cortex (mPFC), anterior cingulate cortex (ACC) and superior parietal lobule are activated when people took either the perspective of others or their-self. Partially brain regions including temporal pole, bilateral temporoparietal junction (TPJ), posterior cingulate cortex (PCC) and posterior superior temporal sulcus (STS) were only activated when people took the perspective of others. However, we didn't know what mechanism was made possible to predict other's preference and temporal information processing as the mechanism is still unknown.

For the analysis of temporal sequence of preference through thin-slicing, electroencephalography (EEG) is the useful tool to measure the temporal information of neural activation. Moreover, the experiment paradigm was composed by acquisition of target person's information and connecting the information of target person and item with EEG measure. Target person randomly presented 9 others and 1 self-picture. Target item was 10 movie posters and 10 food pictures. Overall, 20 number of women responded with a total of 200 trials.

In the results, there are no response time difference between self-trials and other-trials. However, EEG data revealed that difference of left temporoparietal beta oscillation between self-trials and other-trials show significant correlation ($r = -0.8864$, Bonferroni corrected, $p < 10^{-6}$). Subsequently centroparietal alpha oscillation shows the significant difference between other-trials and self-trials until the average time. (Paired t-test, Bonferroni corrected, $p<10^{-6}$)

Each neural evidence in the present study suggests that the period of connecting information of other people and items are more correlated with individual accuracy than the period of others' information acquisition. Results indicate the neural explanation of thin-slicing feasibility. Additionally, thin-slicing is composed of minimum of 2 stages, which are self-referential information processing and social information processing before the response. Self-referential information processing occurs faster than social information processing so self-referential information is ranked higher.

DECLARATION

I, Jonghyeok Park, hereby declare that this thesis, which is fewer than 35.000 words in length, has been written by me, that it is the record of work carried out by me and that it has not been submitted in any previous application for a higher degree at this Institute or any other Institute of Learning.

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ACKNOWLEDGEMENTS

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CHAPTER 1

INTRODUCTION

1.1 Research Background

For survival, some living organisms develop the sharp claw for hunting, wings for flying and create society groups. Among one of the groups are humans, which are one of the most popular living things that builds a community to survive. However, group society for surviving also has disadvantages. Unlike individual life, living things in a group society need additional ability such as social skills for group activities. Argyris defines "social skills as those interpersonal behaviors that enhance the effectiveness of an individual as a member of an organization." [1] Representative social skills are joint attention (JA), social perspective-taking and theory of mind. Joint attention ability is defined as "the capacity to share the perception of a common object with another person." [2] "Social perspective-taking has to deal with the problem of generating more accurate expectations or prediction about the other's behaviors." [3] "Theory of mind allows the individual to be able to assign mental states to himself/herself or to others, such as purpose, intention, knowledge, belief, thinking, doubt, guessing, pretending, feeling, etc." [4] These social skills show the individual differences according to growth environment or character. In addition, these differences of social skills largely affect in how to make social relationships. Therefore, many studies try to verify mechanism and to improve social skills with a behavioral and neuronal perspective.

Many studies of social skills use the various behavioral evidence such as eye-like sensitivity, imitation, biological motion preference, gaze following ability, and face recognition processing. [5- 9] These behavior evidence can be directly observed and measured. Also these abilities are presented from early human life and show more complex interaction as one is growing up. Additionally, these abilities are probably influenced by experience of environment. Hence, behavioral studies help to understand social capacities. (Figure 1.)

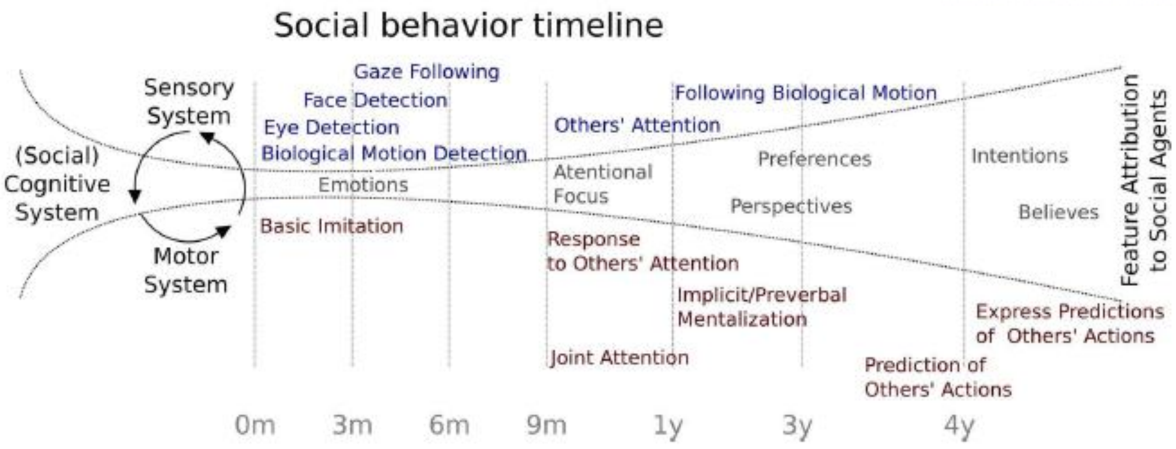

Figure 1. Social behavior timeline [10]

Neuronal studies of social skills mostly use the Electroencephalography (EEG) and brain imaging techniques. EEG is one of the most popular techniques to measure the neuronal activation because it is a non-invasive method to measure the electrical brain activity from scalp electrodes. However, the EEG analysis have some limitations. Skull thickness, myelination and synaptic elimination can influence to the EEG data and we only can measure the brain activation of cerebral cortex. Despite these limitations, the EEG signal, which shows a higher temporal resolution, provides two types of neuronal activity (Figure 2). The first one is event-related potential (ERP) and second one is the analysis of oscillatory brain activity. ERP uses the average of several trials. This process helps to eliminate the interference signals and preserve the signal related to the interest. On the other hand, oscillatory brain activity is not necessary to use phase-locked stimulus. Moreover, it can study spontaneous brain activity. For the brain imaging techniques, many studies use magnetic resonance imaging (MRI) or a functional MRI. These imaging techniques reflect the change of hemodynamic brain response called blood oxygenation level-dependent signal (BOLD), which has a higher spatial resolution (Figure 2). Both EEG and brain imaging techniques can also be directly measured and use to find the neuronal mechanisms of social skills.

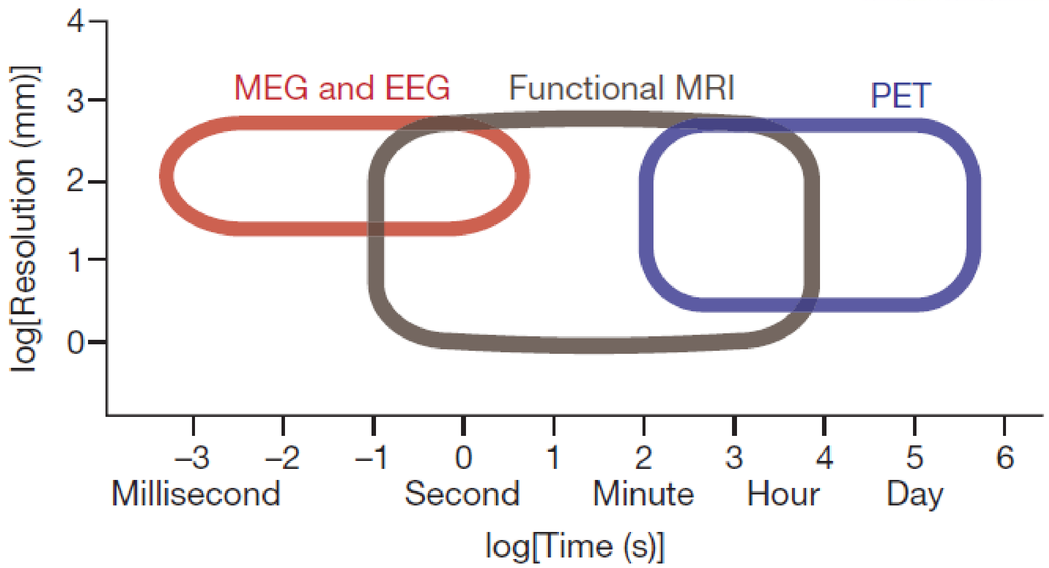

Figure 2. Resolution of neuronal studies apparatus [11]

Although the studies of behavior and neuronal aspects are robustly reported, many neural mechanism of social skills are still unknown. For instance, mirror neuron is one of the most famous research areas because this neuron activates not only movement execution and planning but also observation of others' movement. In addition, suppression of mu rhythm which occurs between a range of 8 and 12 Hz were also reported during these conditions in EEG. However, the neural mechanism that connect with mu rhythms and mirror neuron is still undisclosed. Like this, many social skills still need to study about neural mechanism and thin-slicing process is one of them.

1.2 Literature Review

1.2.1 Theory of thin-slicing

1.2.1.1 Thin-slicing definition

"Thin-slicing" is the one of the social skills to find patterns based on a narrow slice of experience. [12] Even only from a brief observation, humans are often fairly accurate to judge about other people using the thin-slicing. [13-15] The area of altruism, sex orientation, violence or reliability of others are able to be predicted only using restricted slices of experience such as a facial appearance picture, a mute video or a gait pattern. [16-20]. For the explanation of thin-slicing feasibility, a few putative theories have been attempted. The first theory takes an ecological approach and suggests that humans can quickly recognize some features of others (e.g. angry or fear faces) using thin-slices of experience to promote survival and adaptation [21]. The second theory is based on common stereotypes and expectations in others and suggests that humans make an initial judgment based on the memory of common stereotypes and social behavioral conformation to expectations of others [22-23]. The third theory focuses on stimulus information processing and suggests that in the thin-slicing condition, distractors such as excessive thinking of self-presentation is minimized while the capability of dealing with others' information is enhanced [24]. However, any of these theories alone has not sufficiently explained the mechanism of thin-slicing feature.

1.2.1.2 Thin-slicing features

Many studies reported the characteristics of thin-slicing. Hall (1978) said that women have a better ability to decode nonverbal communication than men caused of the traditional social positions of females. [25] Ambady, N., & Rosenthal, R (1992) described several aspects of behavioral characteristic in thin-slicing. [26] The first thing was that observation length of a stimulus showed the independent judgment accuracy through thin-slicing within 5 mins. Another thing was the type of stimuli, whether it is verbal or non-verbal, does not affect the judgment accuracy. The last thing was that additional stimuli such as hearing of speech does not show increase of accuracy but seeing both face and body leads a more accurate judgment than seeing one of them. These results revealed that excessive sensory information can be confused when people judge about other people using restricted information and judgments through thin-slicing and it does not need a prolonged exposure to stimuli to increase accuracy. Albrechtsen et al (2009) described that exposure to 15-s video stimuli led to better discrimination rates than exposure to 3-min video stimuli in social judgment tasks. [27] This result supported these characteristics of thin-slicing.

1.2.2 Thin-slicing category of preference

1.2.2.1 Behavioral processing with Preference

Many types of judgments were reported to be possible by thin-slicing but this study focuses on estimating the others' preferences through thin-slicing [28, 29]. Preference prediction has several features to easily understand about mechanism of thin-slicing. First, preference can be precisely measured as a binary outcome such as likes and dislikes compared to other behavioral aspects such as sex orientation. Second, preference prediction through thin-slicing can easily distinguish two different cognitive processes including the acquisition of others' information and the prediction of their preference by separating the period of target persons information and items to be preferred. One theoretical basis related preference prediction through thin-slicing is the false-consensus effect and projection. [30-33]. These theories described that when a person predicts the preference of others, s/he first considers their own liking and then estimates the others' preferences using perceived difference between the others and their-self. The study from Kurt, D., & Inman, J. J. (2013) have shown that similarities between their-self and others can affect the prediction results. [34] Therefore, processing of the information of both their-self and others may underlie the prediction of what others prefer through thin-slicing.

1.2.2.2 Neural process with Preference

A number of neurophysiological studies have investigated brain regions related to the information processing of their-self and others. Using functional resonance imaging (fMRI) and the experimental designs that separated the perspectives of others and their-self, the previous studies found activation of brain regions including medial prefrontal cortex (mPFC), anterior cingulate cortex(ACC) and superior parietal lobule when people took either the perspective of others or their-self. Partially brain regions including temporal pole, bilateral temporoparietal junction (TPJ), posterior cingulate cortex (PCC) and posterior superior temporal sulcus (STS) were only activated when people took the perspective of others. Otherwise activation of right insula was only shown when people took the perspective of their-self. Like this, some common or each activated brain regions could be induced by perspective of others and their-self [35-43]. In addition, similarly, Kang et al suggested that mPFC activity is related to information processing of perspective of their-self and others whereas connectivity between mPFC and lateral cortical activity such as right TPJ and PCC is related to thin-slicing accuracy [28].

1.3 Research Rationale

Literature review showed that behavioral thin-slicing features such as the effect of gender, independency of exposure time, stimuli type and inefficiency of excessive information. However, there are still remains in neural mechanism of the thin-slicing that need to be clarified.

Kang et al (2013) suggested the neural process of thin slicing when a participant estimates others' preferences. They reported that the region of mPFC is the core system of information processing for perspective of their-self and others. Right TPJ and PCC assist the higher order information processing which correlated with thin-slicing accuracy.

However, compared to neural mechanism evidence about spatial aspects through thin-slicing, temporal aspects of neural mechanism are still unknown despite the peculiarity of temporal information processing. This study therefore provides temporal process of thin-slicing during others' preferences estimation in EEG. The findings of this study will contribute to understand why thin-slicing, which we can't clearly explain, was possible.

1.4 Research Objective

This study aims to investigate how brain activity evolves over a short period of thin-slicing when a person processes information relevant to the prediction of preference. To this end, first, we analyze the temporal sequence of brain signals using electroencephalography (EEG) as EEG has a higher temporal resolution than fMRI and thus would be more suitable to examine time-varying brain patterns over a short period. Previous studies revealed that social skills such as recognizing others' facial emotions are accompanied by increases in the magnitude of alpha oscillations in EEG [44-45]. EEG beta oscillations have also been used for predicting one's preference on movie trailers or musical tempo [46-47]. Therefore, we hypothesize that temporal patterns of EEG oscillations can probe the temporal sequence of brain activity related to prediction of others' preferences through thin-slicing. Second, we compare EEG oscillations when a person predicts others' preferences and when she reports their self-preference to see how neural information processing of their-self and others influences predictions. In the experimental design, we include epochs where a person reports their own preference for the items that she/he also predicts the target person's preference. Based on the theory of thin-slicing focusing on stimulus information processing [24], we hypothesize that differences in EEG oscillations between self-information processing and others' information processing would be correlated with one's ability to predict others' preferences.

In summary, this study suggest the two hypotheses as follow:

Hypothesis 1: Temporal pattern of EEG oscillation can prove the temporal sequence of thin-slicing during others' preferences estimation.

Hypothesis 2: Self-information processing can affect the others' information processing during thin-slicing.

CHAPTER 2

PREFERENCE ESTIMATION IN THIN-SLICING PROCESS FROM EEG DATA ANALYSIS

2.1 Method

2.1.1 Experiment: Preference estimation test

2.1.1.1 Participants

Twenty right-handed female undergraduate students participated in this study (average age: 21.86, range: 20-25). All participants had no medical history of neurological illness or damages and did not take any psychiatric medicine. All participants were able to keep their bodies still for a long time and fully recognize prediction items (i.e. movie, food). Each participant received a monetary reward of 20,000 KRW after the study. {UNISTIRB-15-04-C}.

2.1.1.2 Instruments

EEG reflects the summation of the synchronized activity of neurons that are located in a similar region and most of EEG signals are made by pyramidal neurons. One of these signals require many precautions when measured because it is very tiny. Moreover, Ag/AgCl electrode which shows minimally polarizable was used for acquiring of brain electric activity change. For the each electrode's signal, EEG instrument calculates the two differences. First potential difference between scalp electrode and ground was measured. The second potential difference between reference electrode and ground was also measured. Finally, the difference of two potential differences was recorded as each electrode's signal.

2.1.1.3 Stimuli

All stimuli photographs were face, movie poster and different types of food with 720x480 pixels size. The face pictures containing neutral face, shoulder, slight smile and gray backgrounds were composed of nine others and one self-picture. Others like movie posters and food pictures were offered by Kang's study. [28] Other face pictures were selected by a pre-test. A total of 56 students (27 males, mean: 22.78 years, std: 1.95 years) were recruited for selecting 9 final facial pictures. Selecting criteria was high facial appearance between-variability and within-variability of preference about food, movies, bags, shoes and books as well as the self-picture that was taken. The movie and food photos are also selected by a pre-test. A number of 18 participants were recruited for evaluating 5 categories, which are composed of food, movies, bags, shoes and books. A total of 280 evaluated photographs samples were collected for a 4-scale evaluation which start from the range of 1(strongly hate) to 4(strongly like). After that, only 10 samples for each of the categories using medium level of average and high variance were selected. However, only 2 categories (movie and food) were used as the stimuli, because only these categories show the higher other-preference prediction accuracy than chance-level in previous studies. Finally all of the photographs were adjusted into an identical frame.

2.1.1.4 Experiment design and procedures

2.1.1.4.1 Experiment design

After arriving at the laboratory, participants received detailed verbal instructions about the procedure and purpose of the experiment. Participants sat on a chair and rested for the EEG setting for 30 minutes. Then, they practiced several trials for preventing errors caused by the unfamiliar stimulus. Next they entered the main experiment as the whole experiment has two blocks which were composed of food and movies with no break time. The order of these sessions was randomized and each session had 100 trials with no feedback condition. Each trial began with a baseline period in which a black fixation cross appeared on the center of a white screen for 3 s. The size of the fixation cross was 30 x 30 pixels (visual angle: 1.528∘). Then, the preference prediction task period followed. The task period was composed of two disjoint segments. In the first segment, participants acquired the information of the target person. (Face phase) The target person was composed by self-photographs (Self-trials) and other photographs. (Other-trials) This order was also randomized. Participants were shown the picture of the target person for 3 s, which was located in the center of the screen. The second segment follows immediately after the first segment in which participants were shown the picture of an item. (Item phase) The item picture appeared in the center of the screen until the end of the second segment. The second segment ended either when participants’ response was detected or when 5 s elapsed from the onset of the second segment. Participants provided their prediction response by pressing the designated keyboard buttons. The trial was deemed to fail when participants could not provide their prediction response within 5 s. Participants predicted the preference of the target person for the item by choosing one of four responses which is written in Korean: 1) very dislike, 2) dislike, 3) like, and 4) very like (corresponding keyboard buttons were D, F, J, and K, respectively). For instance, pressing the “very like” button (keyboard button “K”) recorded participants’ prediction that the target person would like the item very much (Figure 3). Every possible pair of the target person and the item was presented to participants in a random order. A total number of trials was 200 (10 targets x 20 items). The average time taken for a single trial was 7.5628 ± 0.2242s. The inter-trial interval was the same period of fixation.

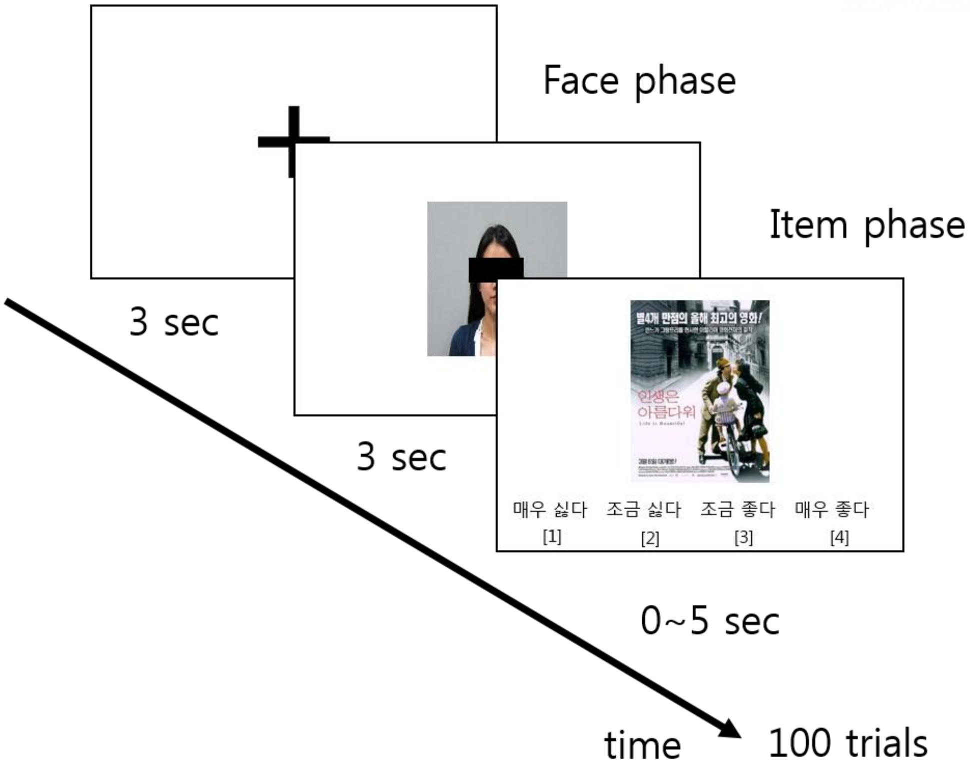

Figure 3. Experimental paradigm

Figure 4. Stimuli sets of prediction item

2.1.1.4.2 EEG recording preparation and calibration

The EEG signals of each participant were acquired during the entire experimental period using 32 Ag-AgCl referential active electrodes placed on the actiCap, amplified by BrainVision actiChamp [Brain Products GmbH, Gilching, DE]. The sampling rate was 500 Hz. A total of 19 electrodes were placed on the surface of the scalp following the international 10-20 system. The electrode positions, identified by the EEG cap provided by the EEG device maker, were FP1, FP2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1 and O2. The ground electrode was placed at the position of FPz. A reference electrode was placed on the right ear. A conductance gel (SuperVisc 1000gr, Brain Products) was inserted between each electrode and the surface of the scalp. The impedance was maintained below 10kΩ throughout the recording.

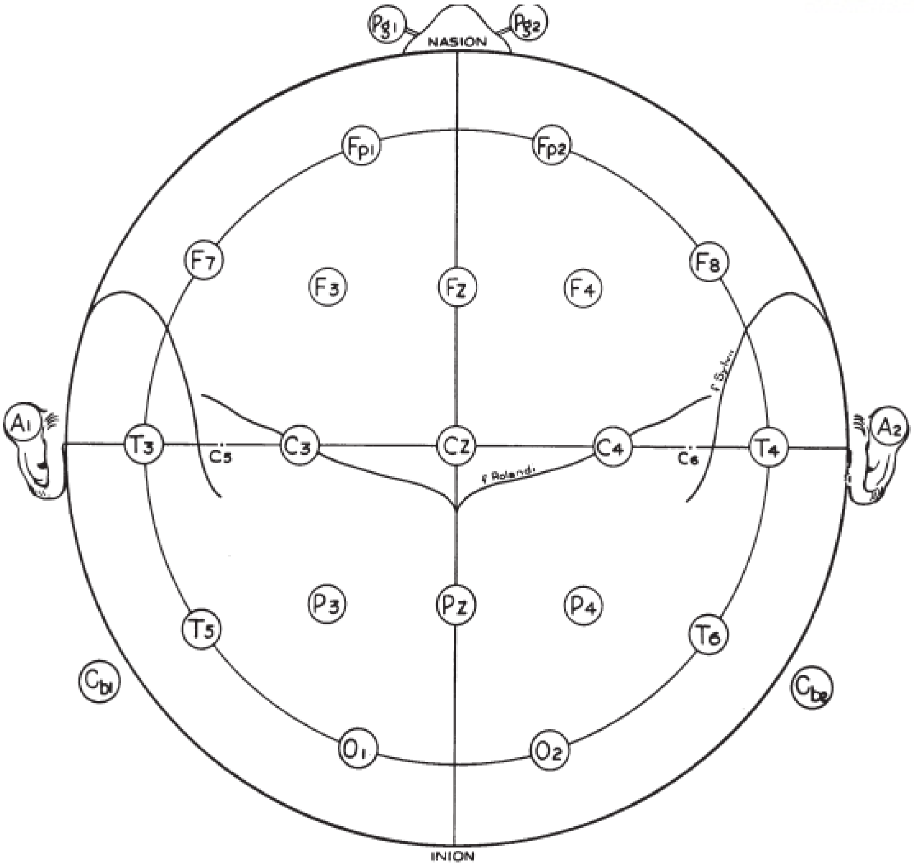

Figure 5. EEG channel location of 10-20 system [48]

2.1.2 Data Processing and Analysis

2.1.2.1 Filtering

Recorded EEG signals were filtered using a Butterworth filter. The cut-off frequency of 0.1Hz and 50Hz were used and 4-order zero-phase IIR filter was used for avoiding noise signals such as 60Hz.

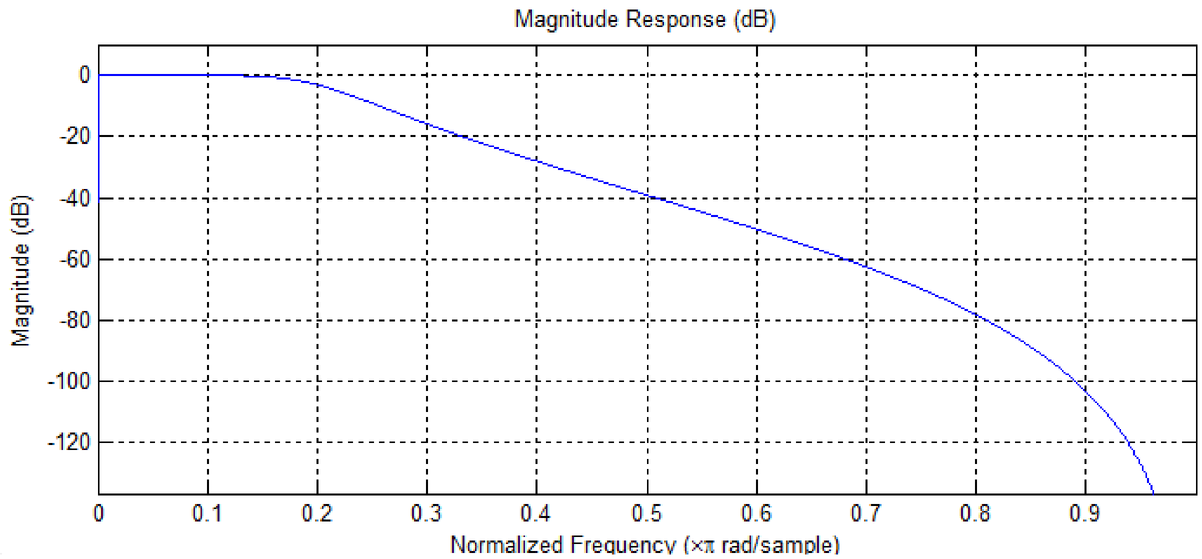

Figure 6. Magnitude response graph of filter

2.1.2.2 Epoching

For the EEG analysis, we need to divide of informative periods. Each trials were composed by 1s baseline period, 3s acquisition of others' information period and 3s connecting the information of the other persons and objects period. Thus, a single epoch totally have 7s length. Every epoch was classified as one of the two conditions which were self-preference report conditions and others' preference estimation conditions.

2.1.2.3 Short-time Fourier Transform

For analyzing the oscillation activity of EEG signal, all participants and channel EEG data were transformed to time-frequency domain using short-time Fourier transform (STFT). This method was used with a 0.5-s hamming window, 0.4-s overlap and the frequency resolution was 1.9531 Hz. Moreover, STFT yielded 66 windows x 129 frequency components firstly in each epoch. However, EEG data was filtered below the 50 Hz frequency. This yield a 19 channel, 25 frequency and 66 time windows matrix. The Welch's power spectral density estimation of each frequency component at each time window was obtained for each epoch and averaged over all the epochs belonging to each condition. Before the statistical analysis, we assumed that the result of EEG data would show a continuous significant interval of more than 0.5 sec and 4 Hz. Thus, an area of 5 windows x 3 frequency components processed the moving average. Finally, in each participant there were two conditions, a 19 x 23 x 61 time-frequency data matrix.

2.1.2.4 Behavior data analysis

For the calculation of prediction accuracy, each participant's response was compared with pre-recorded true preference response of the target person. We rearranged the four types of response to binary response as either "like", including both "strongly like" and "marginally like", or "dislike", including both "strongly dislike" and "marginally dislike" to simplify calculation. Then we matched these simplified responses between the target persons and each participant for every item. We excluded those trials where no response of participants was obtained before the 5-s time limit. Consequently, 99.4 $\pm$ 1.3917 responses on average for food and 99.9 $\pm$ 0.3078 responses on average for movies were included in the analysis of accuracy. Also, we measured response time (RT) for each trial and analyzed a difference in RT between the other-trials and the self-trial using a paired t-test.

We did not use a simple 50% chance level because the bias of the target person's responses in a particular category could occur. The chance level of prediction accuracy was generated by a random guess using the participant's response. We first shuffled the order of the original preference prediction response by the participant for generating a set of pseudo-random prediction data. Then we compared the shuffled data with the true target person's data. This process made a one pseudo-random prediction accuracy and we repeated 1000 times to create a distribution. After that, these distributions were sorted by numerical order for linear interpolation. Each element was assumed to be equally spaced from 0.05% to 99.95%. Then, we estimated the 95% level using a linear equation. This estimation of the chance level was conducted for every pair of participant and category.

2.1.2.5 Paired t-test

Paired t-test was used for analyzing within-subject difference in EEG spectral power between two conditions (self-preference report vs. others' preference predictions). Null hypothesis was the difference between two conditions that come from a normal distribution with equal mean to zero and unknown variance. These analyses were performed for each combination of time-frequency independently. This test aim to find the different brain oscillation patterns between others information processing and self-information processing.

2.1.2.6 Pearson correlation

Pearson correlation was used for analyzing relationship in EEG spectral power with behavioral results. Significant level was computed by transforming the correlation to create a t statistic having n-2 degree of freedom. These analyses were performed for each combination of time-frequency independently. This test was used to examine which periods was the salient period for determining the prediction accuracy between acquisitions of the information of other persons and connecting the information of the other persons and objects.

2.1.2.7 Bonferroni-correction

Each EEG time-frequency component made the hypothesis for finding significant difference or correlation. Moreover, significant level was changed from 0.05 to 0.05 divided by 19 channels, 23 frequency components and 61 windows.

2.2 Results

2.2.1 Response time

The comparative analysis of response time between the Self-trials and Other-trials conditions revealed no significant difference. (Self: 1,572.1 ± 277.5 ms, Other: 1,590.2 ± 230.0 ms, $p = 0.6939$). Additionally, response time between the movie stimuli and food stimuli also revealed no significant difference. (Food: 1,549.4 ±277.5 ms, Movie: 1,588.4 ± 227.2 ms, p= 0.4261)

2.2.2 Others' Preference estimations accuracy

When predicting others' preference of movie, 10 out of 20 participants showed significantly higher prediction accuracy than chance (permutation test, 95% significance level) (Figure 1). On the contrary, when predicting others' preference of food, only two participants showed significantly higher prediction accuracy than chance (permutation test, 95% significance level). Thus, we excluded the data of food preference out of the subsequent EEG analysis.

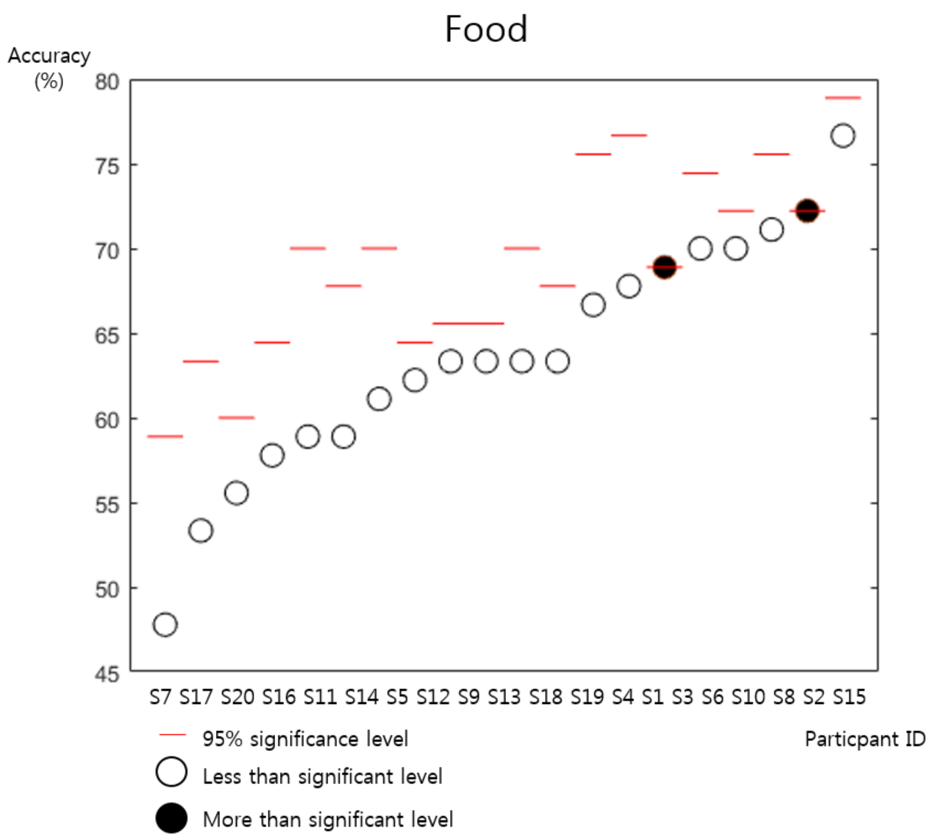

Figure 7. Result of behavior response in food stimuli

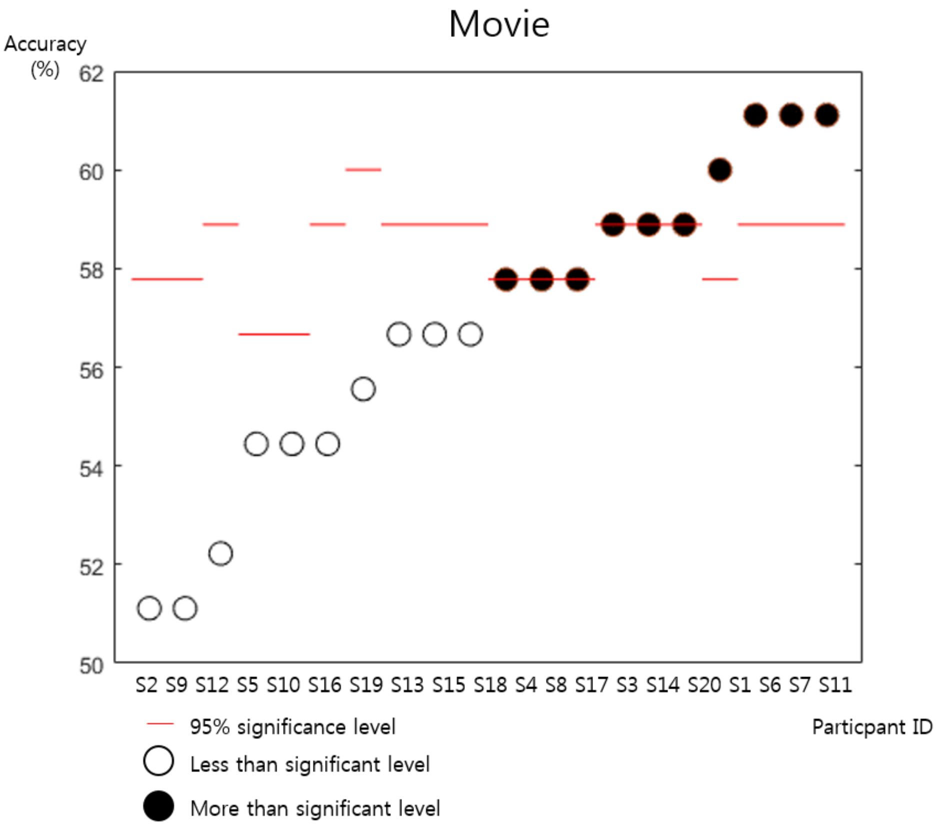

Figure 8. Result of behavior response in movie stimuli

2.2.3 EEG difference

2.2.3.1 Difference between self-preference report and others' preference estimation

We analyzed EEG oscillations for each condition of reporting self-trials and other-trials, respectively. In both conditions, there was a clear increase in power (Event-related synchronization; ERS) in the alpha frequency band (7 – 12 Hz) over the parietal region during the first segment when participants were shown the target person's picture. During the second segment, however, alpha ERS was present over the middle and right parietal regions (Pz, P4, T6) only for the condition of predicting others' preferences. We observed significant differences of alpha power between the conditions during this specific period, 0.6~1.1 seconds after onset of an item appearance in the second segment, in those 3 channels, including Pz, P4 and T6 (paired t-test, Bonferroni corrected, $p < 10^{-6}$) (Figure 23, 24, 25).

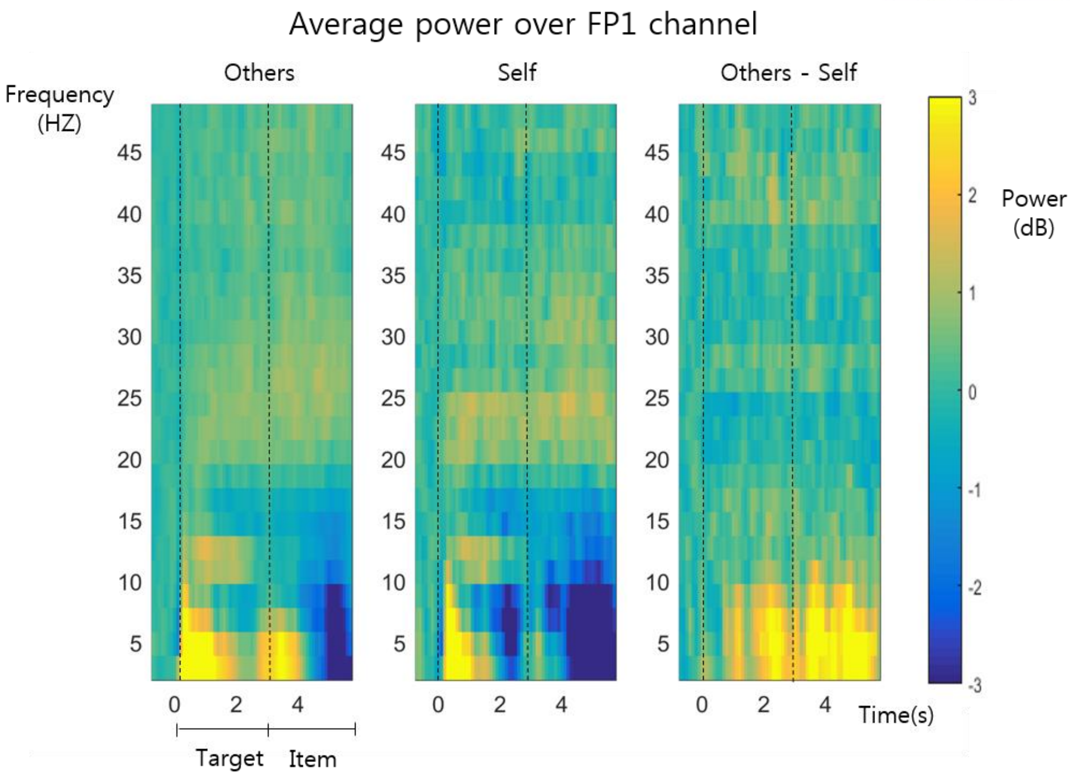

Figure 9. FP1 Spectral power of each condition (left: others, middle: self, right: difference)

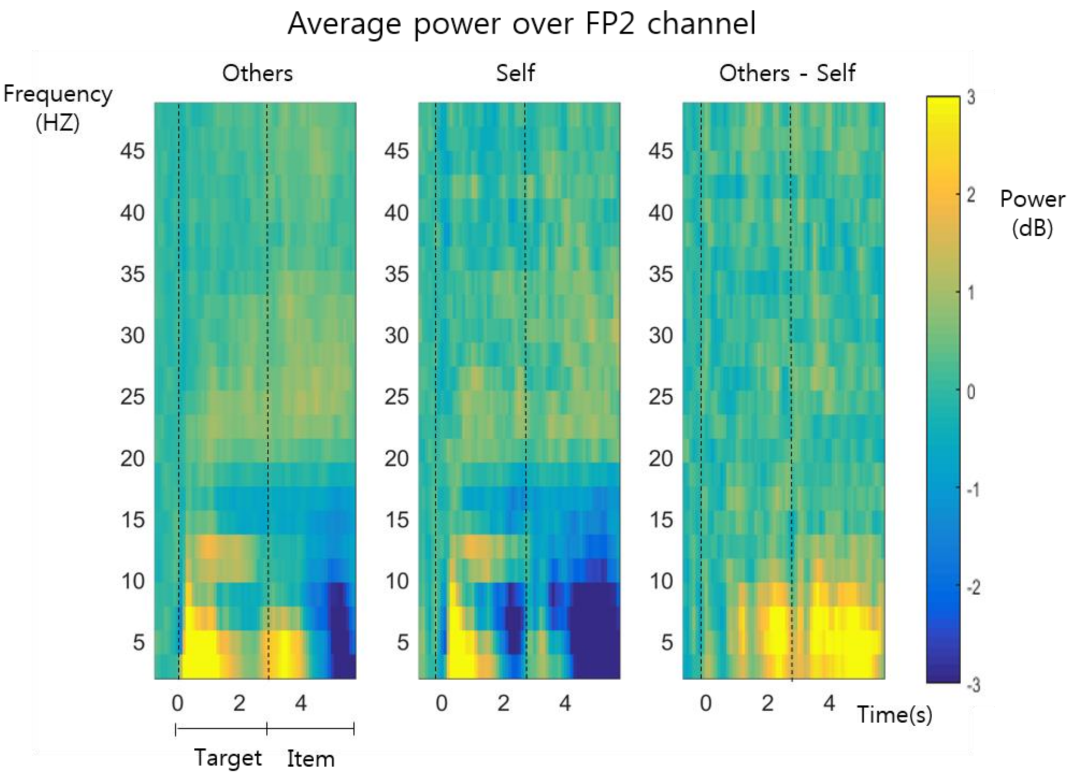

Figure 10. FP2 Spectral power of each condition (left: others, middle: self, right: difference)

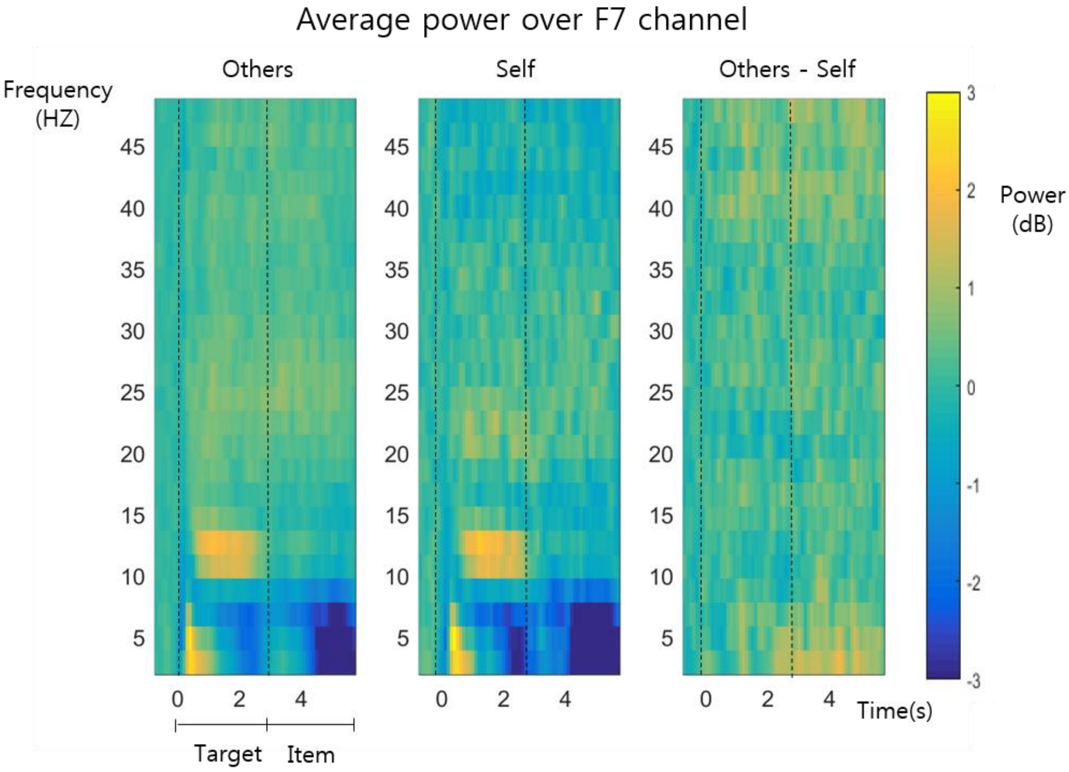

Figure 11. F7 Spectral power of each condition (left: others, middle: self, right: difference)

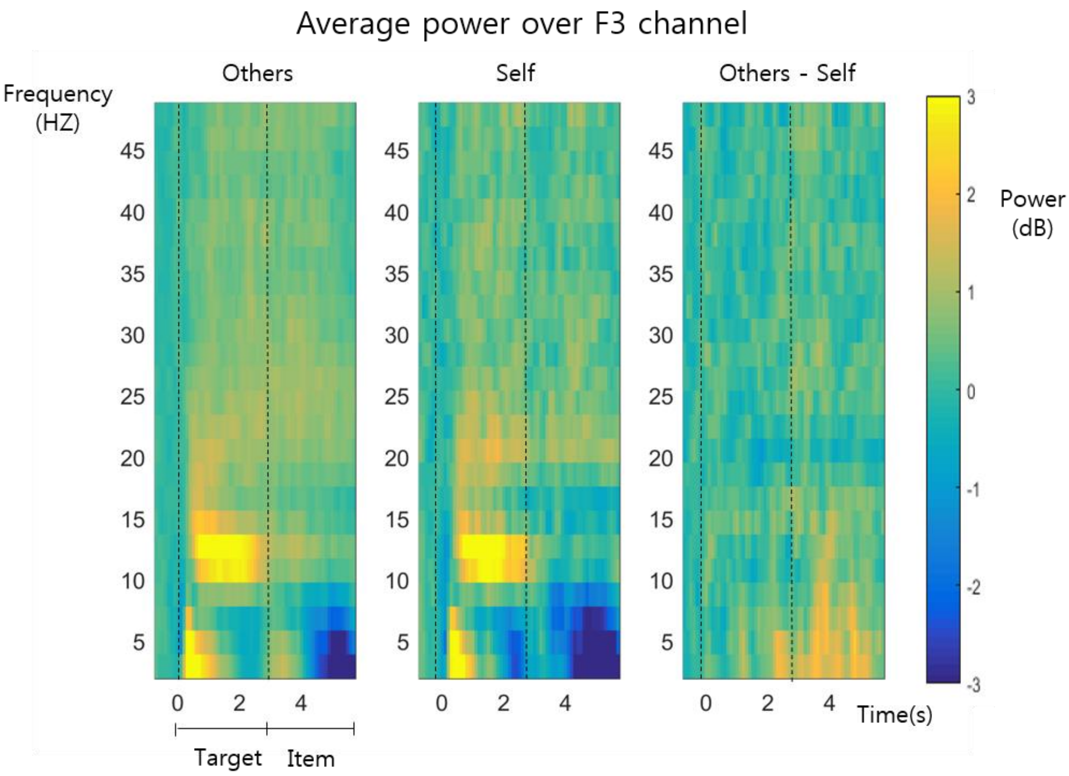

Figure 12. F3 Spectral power of each condition (left: others, middle: self, right: difference)

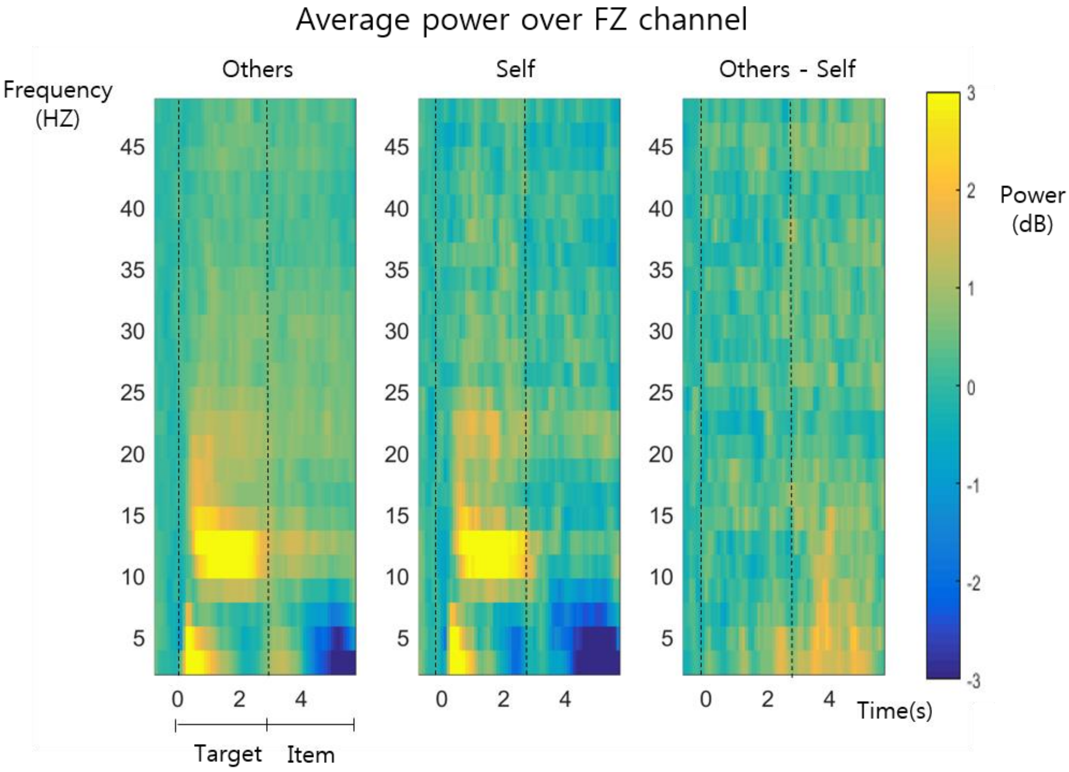

Figure 13. Fz Spectral power of each condition (left: others, middle: self, right: difference)

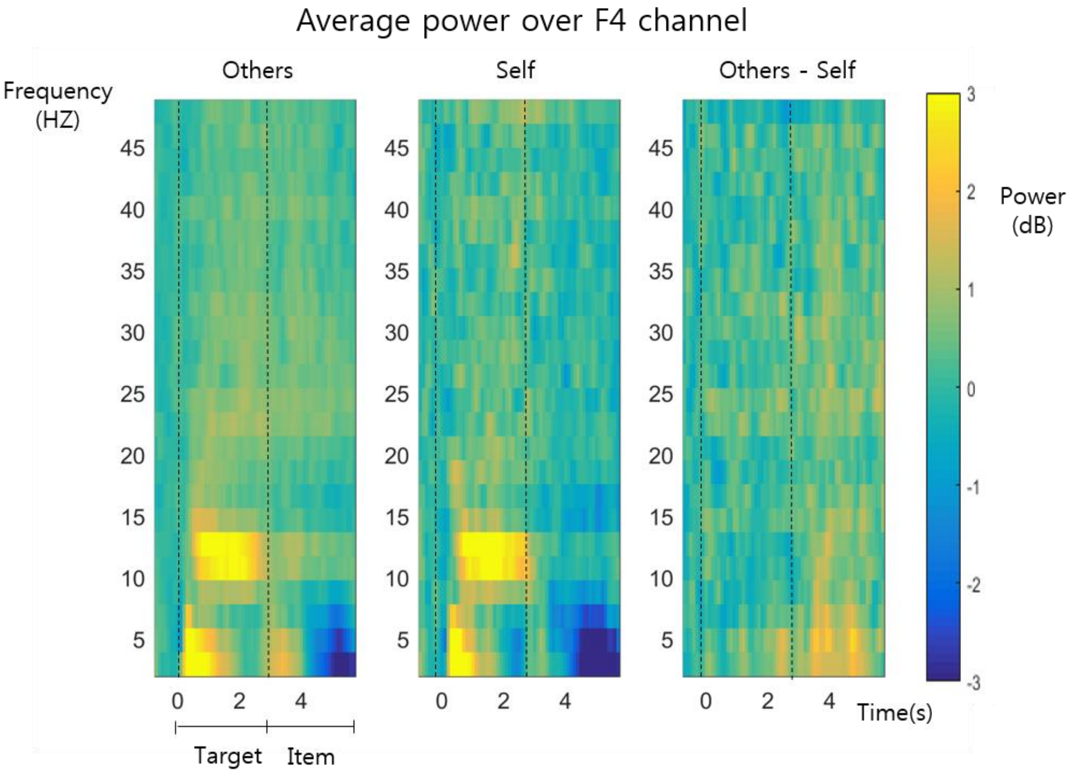

Figure 14. F4 Spectral power of each condition (left: others, middle: self, right: difference)

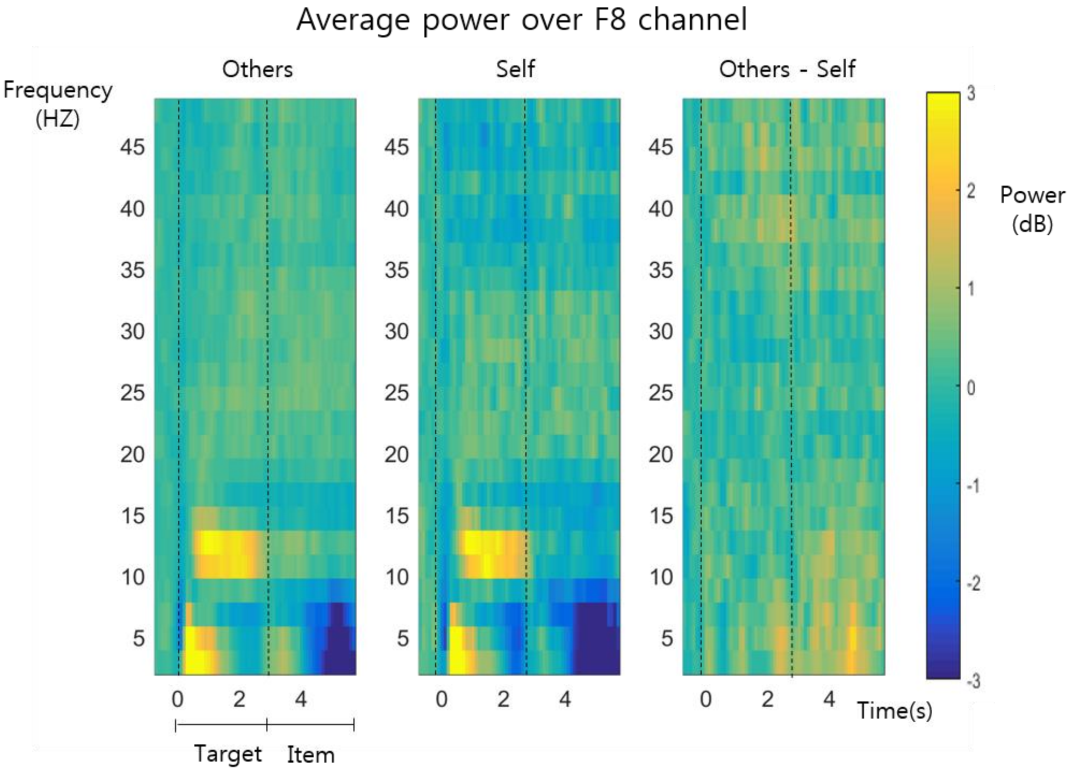

Figure 15. F8 Spectral power of each condition (left: others, middle: self, right: difference)

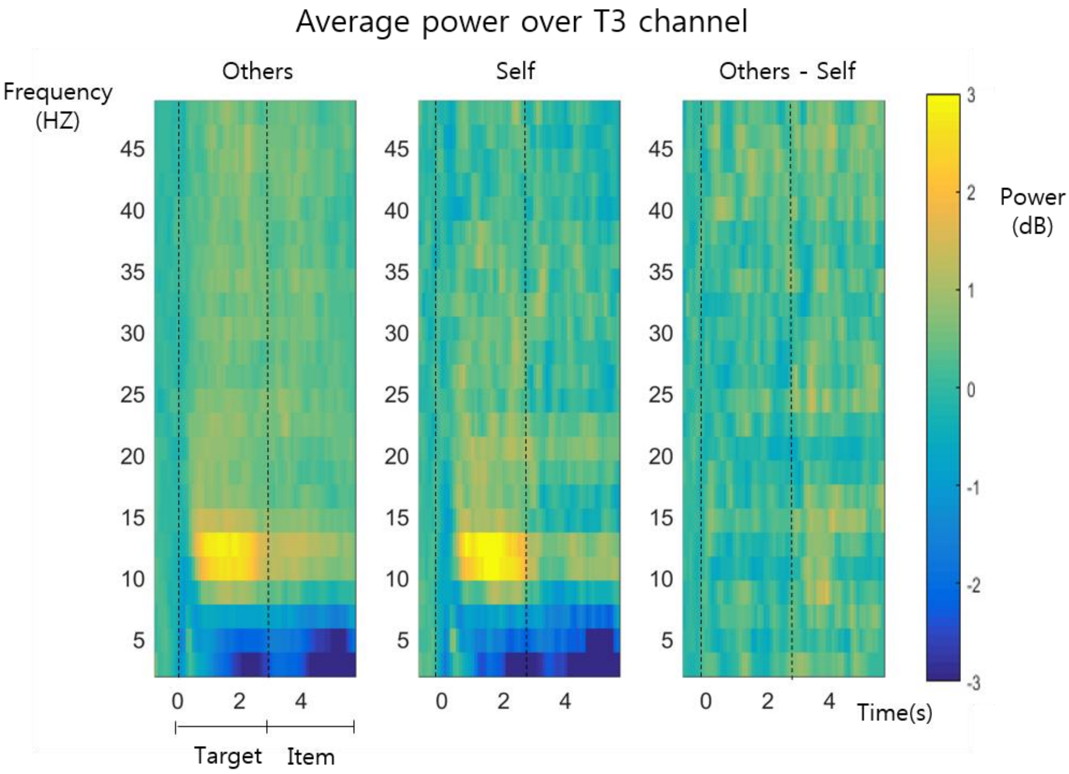

Figure 16. T3 Spectral power of each condition (left: others, middle: self, right: difference)

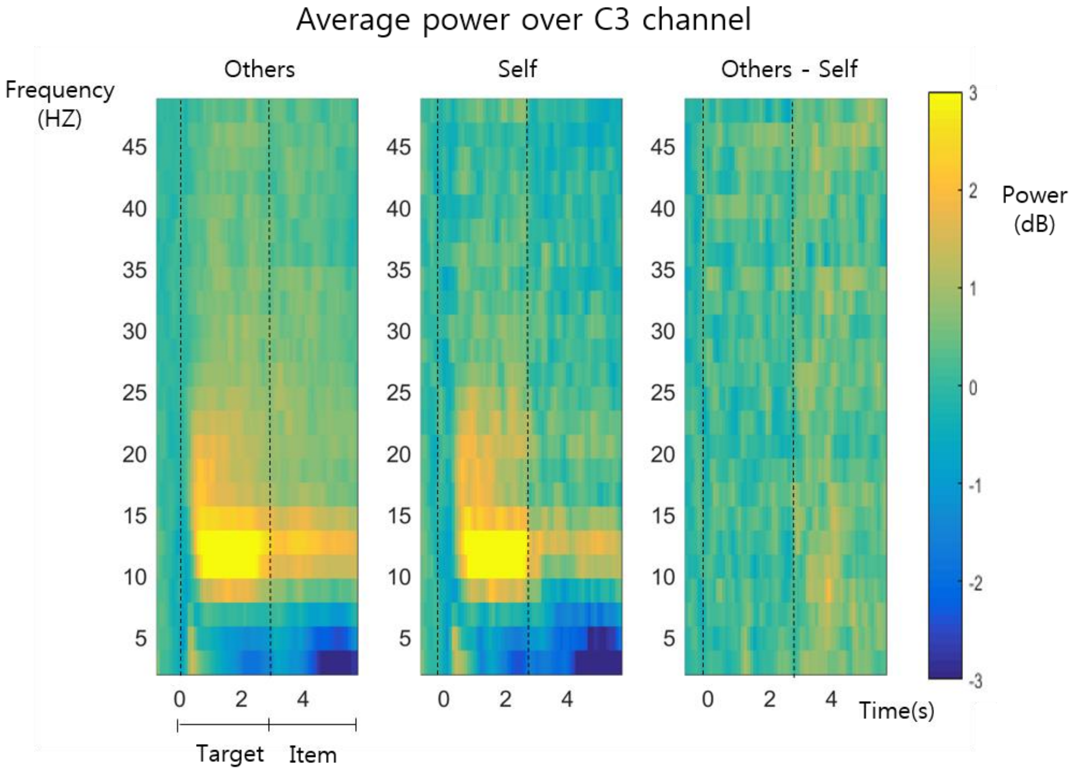

Figure 17. C3 Spectral power of each condition (left: others, middle: self, right: difference)

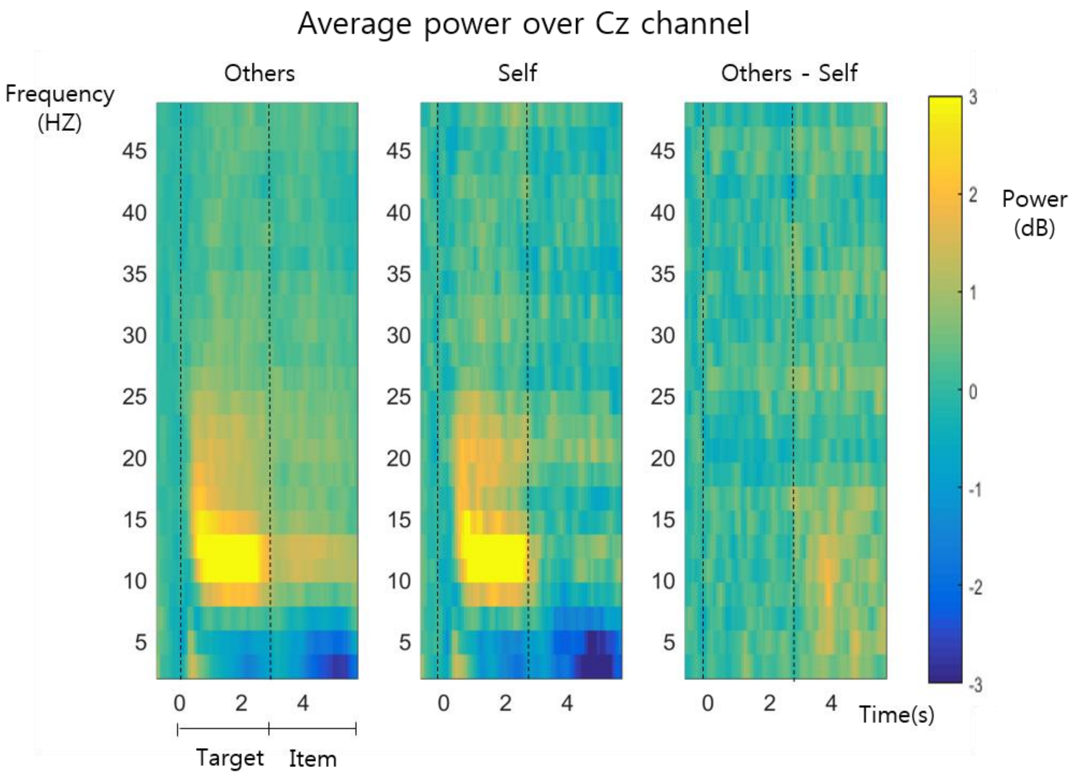

Figure 18. Cz Spectral power of each condition (left: others, middle: self, right: difference)

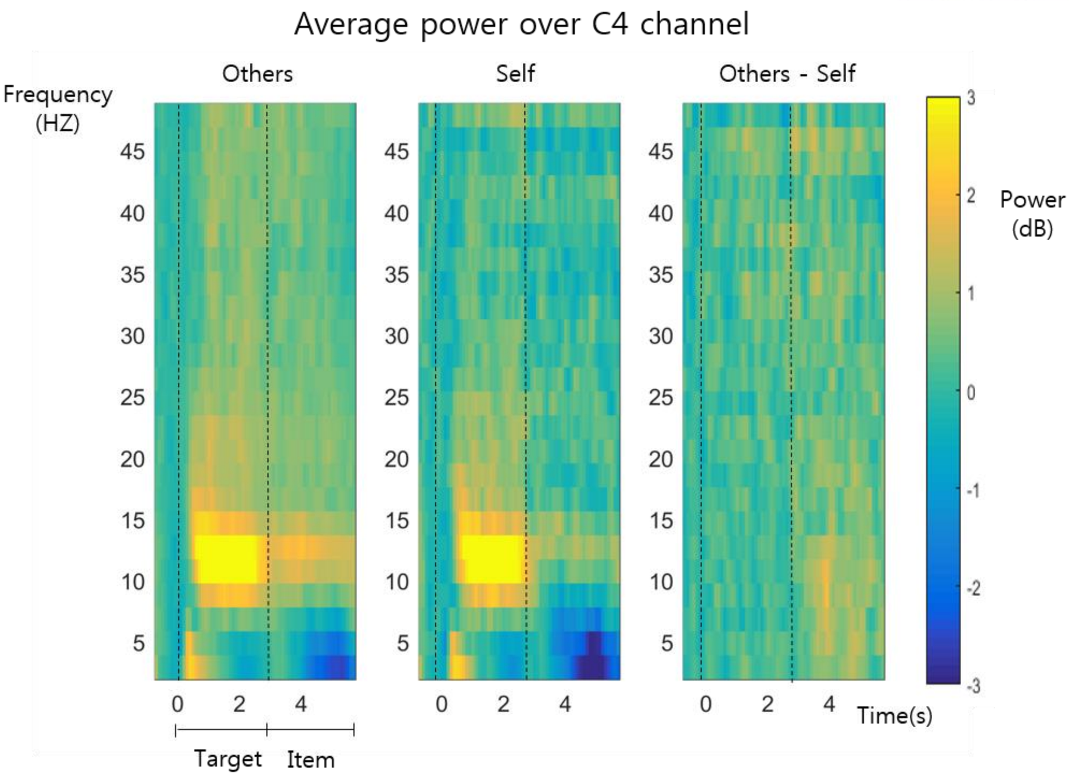

Figure 19. C4 Spectral power of each condition (left: others, middle: self, right: difference)

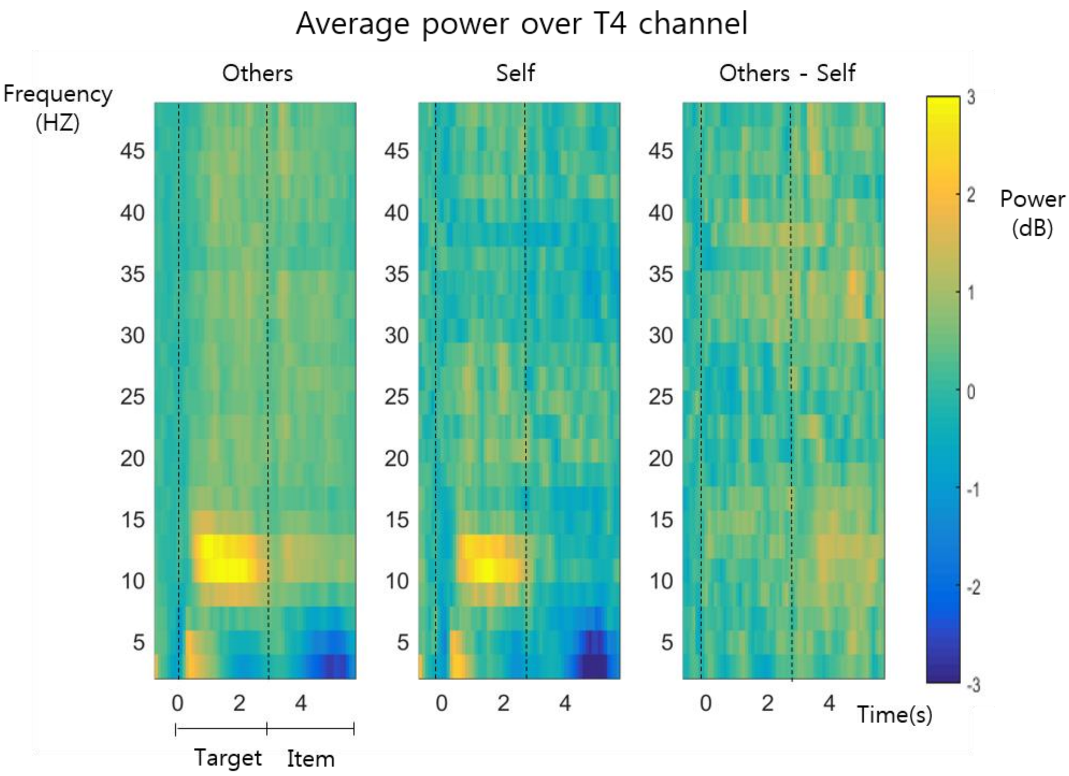

Figure 20. T4 Spectral power of each condition (left: others, middle: self, right: difference)

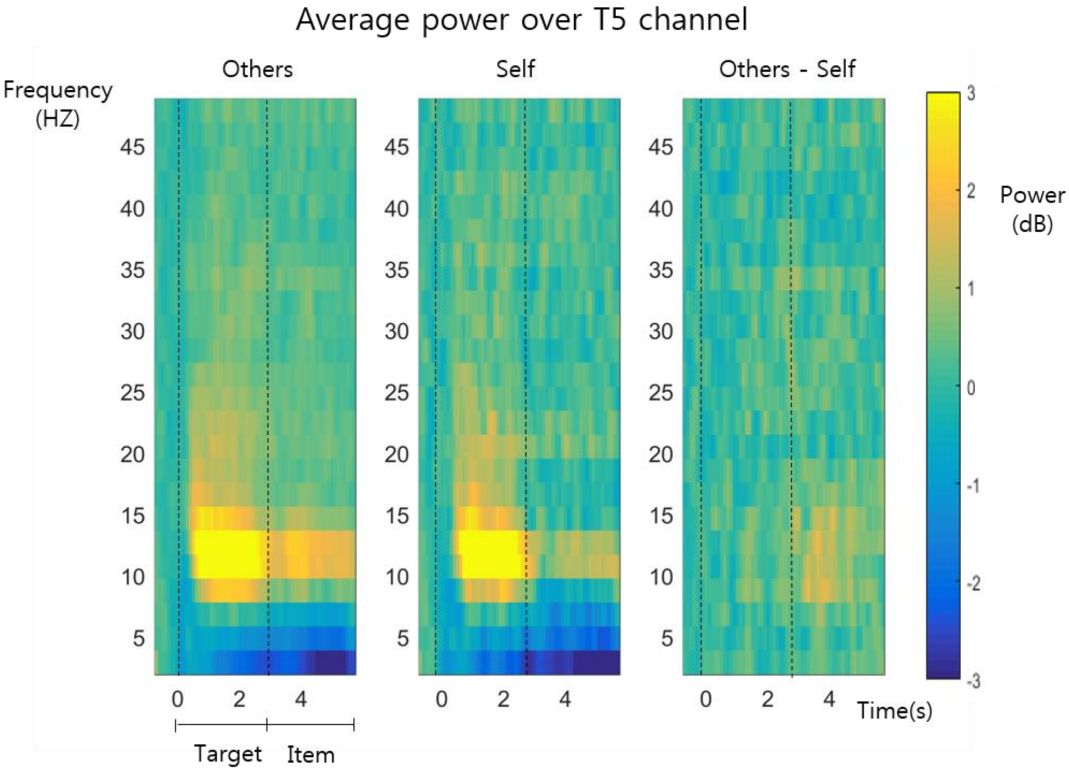

Figure 21. T5 Spectral power of each condition (left: others, middle: self, right: difference)

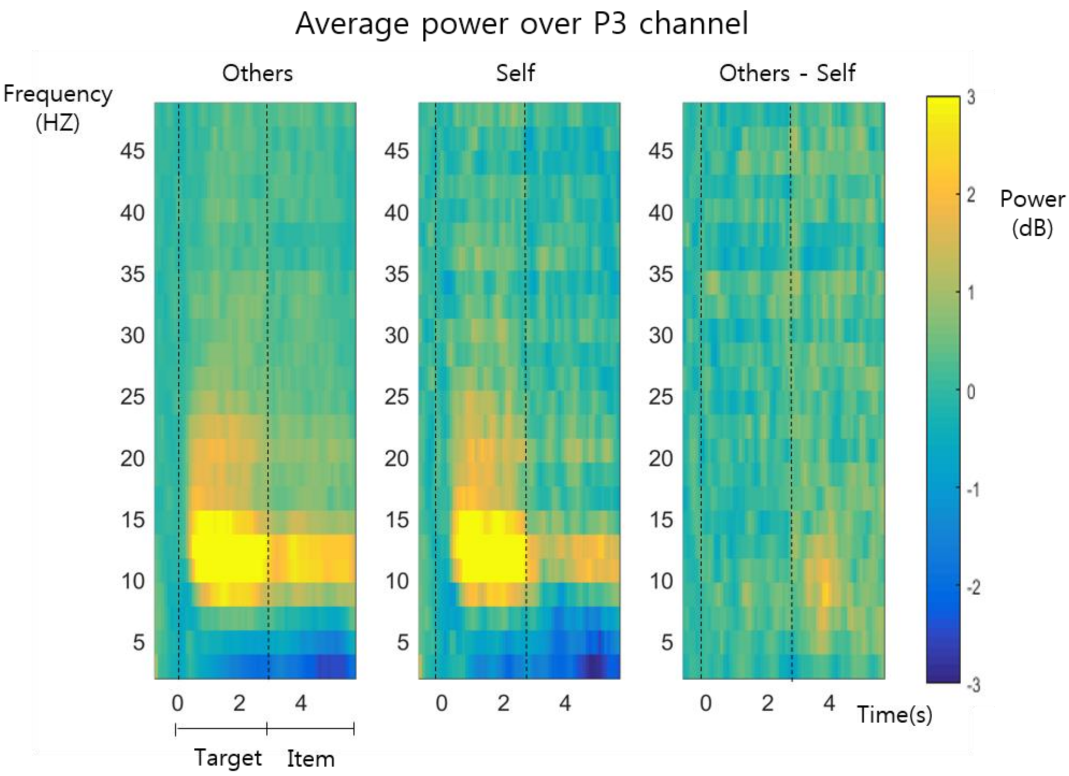

Figure 22. P3 Spectral power of each condition (left: others, middle: self, right: difference)

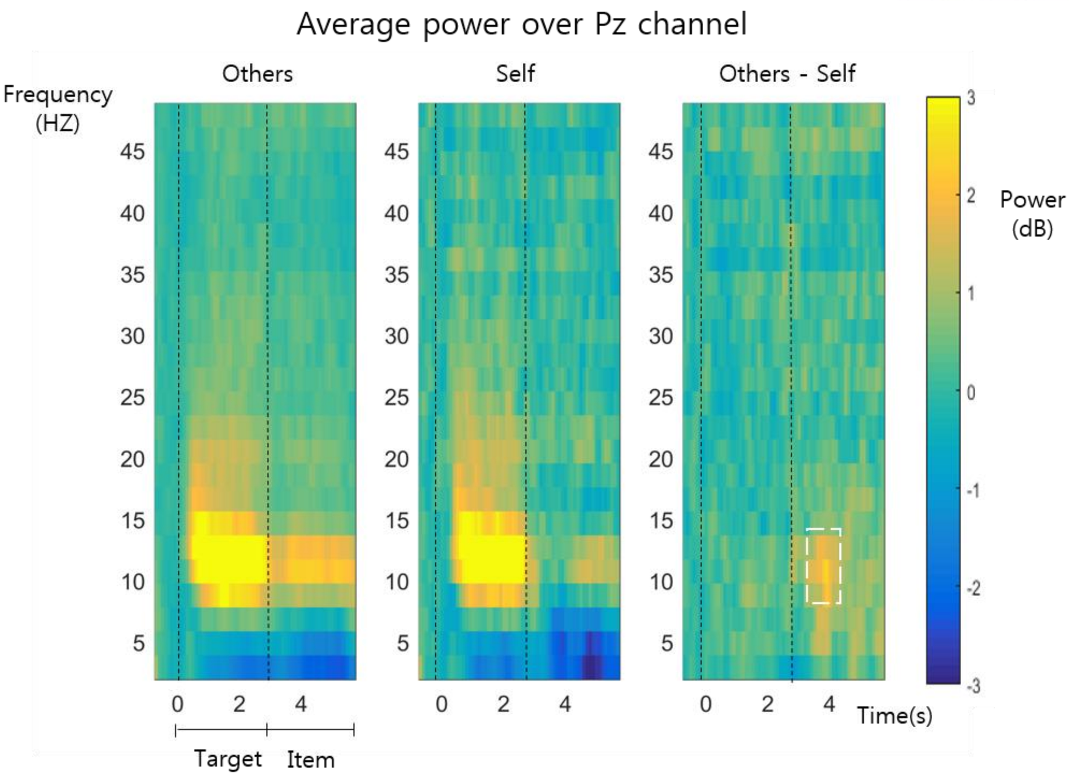

Figure 23. Pz Spectral power of each condition (left: others, middle: self, right: difference, white dash box: significant area)

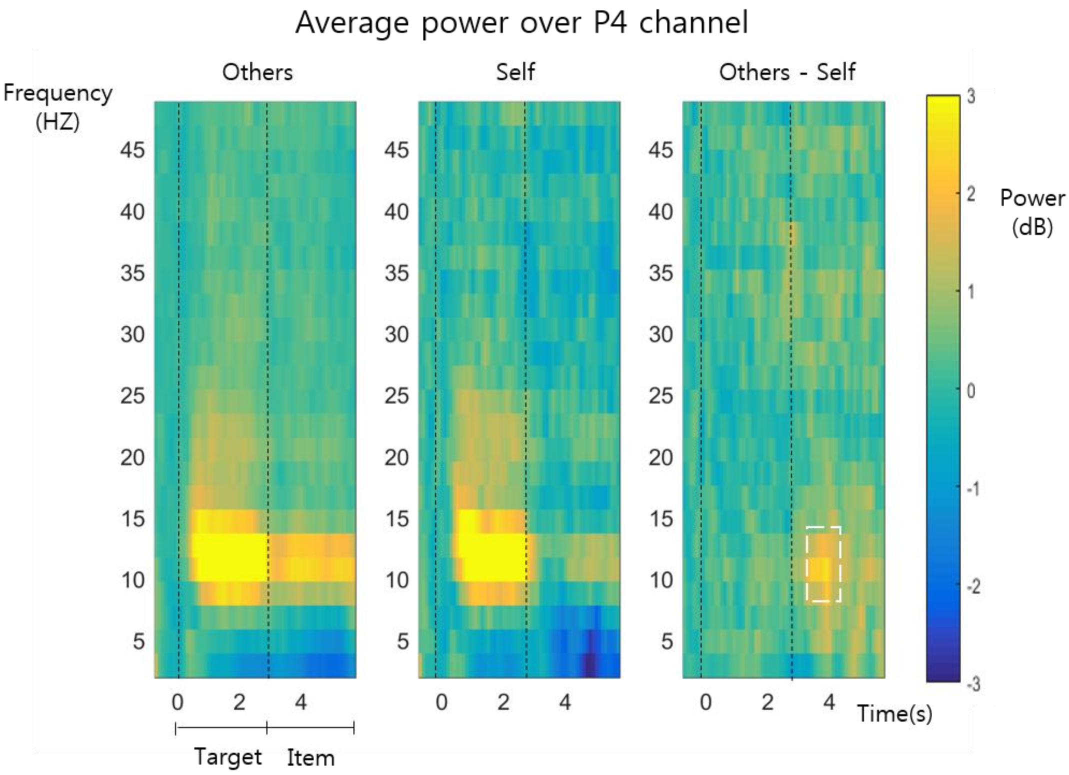

Figure 24. P4 Spectral power of each condition (left: others, middle: self, right: difference, white dash

box: significant area)

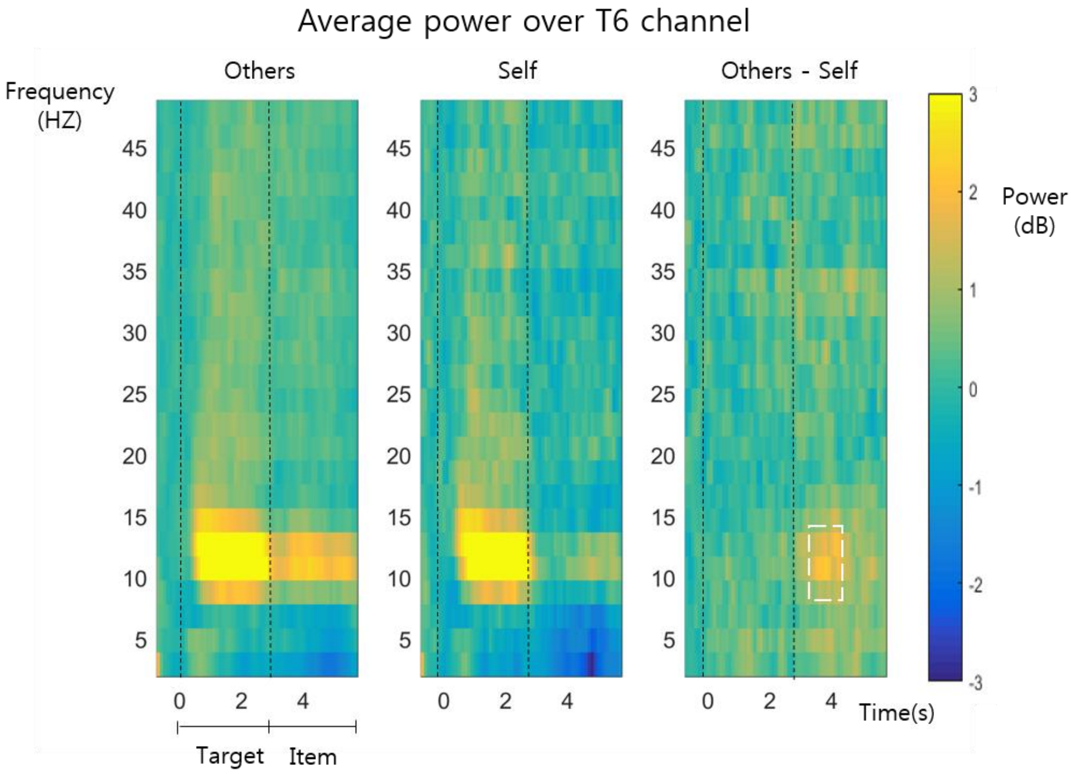

Figure 25. T6 Spectral power of each condition (left: others, middle: self, right: difference, white dash box: significant area)

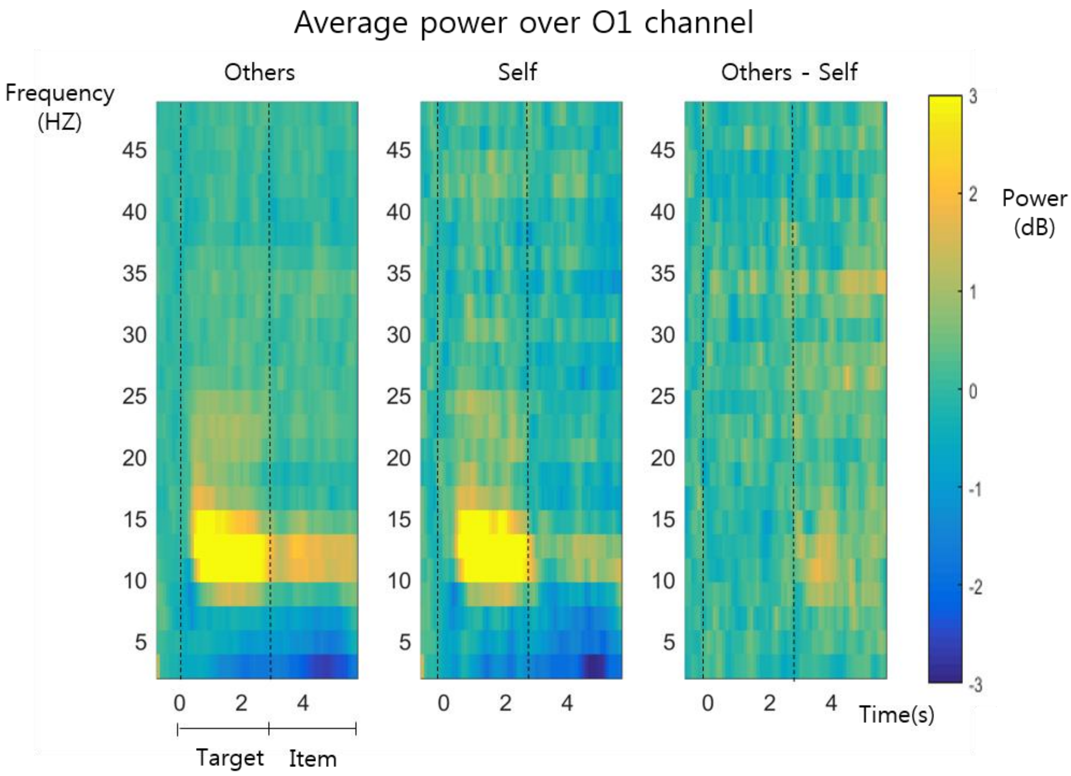

Figure 26. O1 Spectral power of each condition (left: others, middle: self, right: difference)

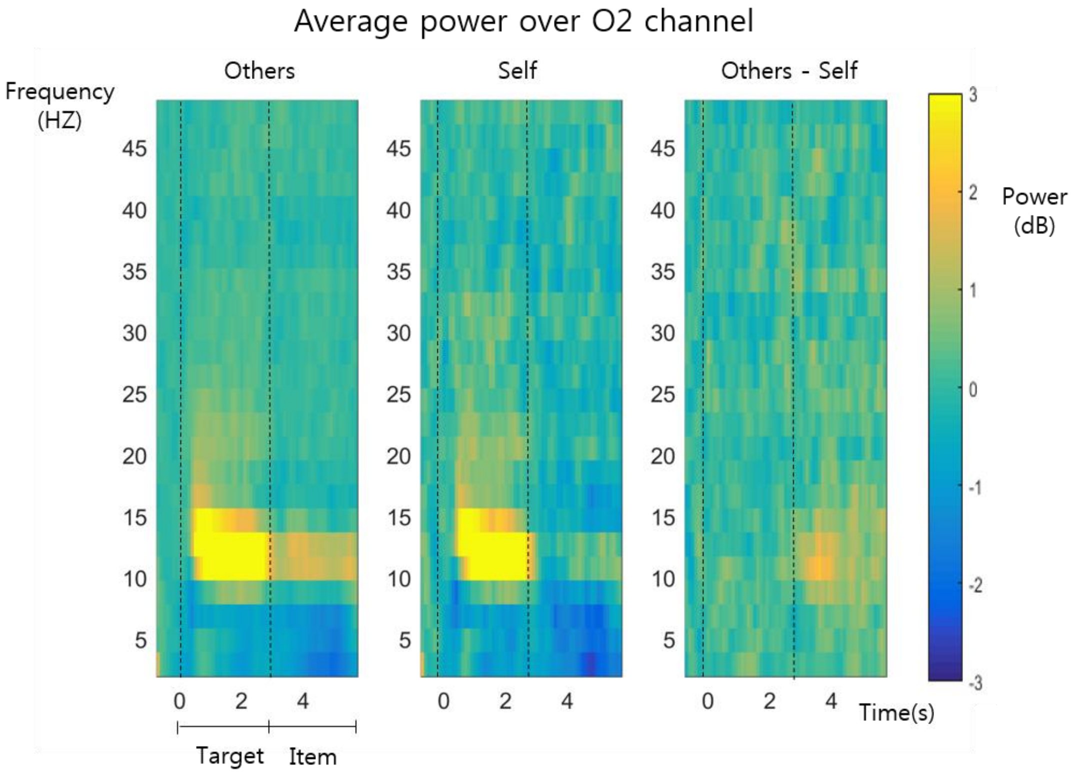

Figure 27. O2 Spectral power of each condition (left: others, middle: self, right: difference)

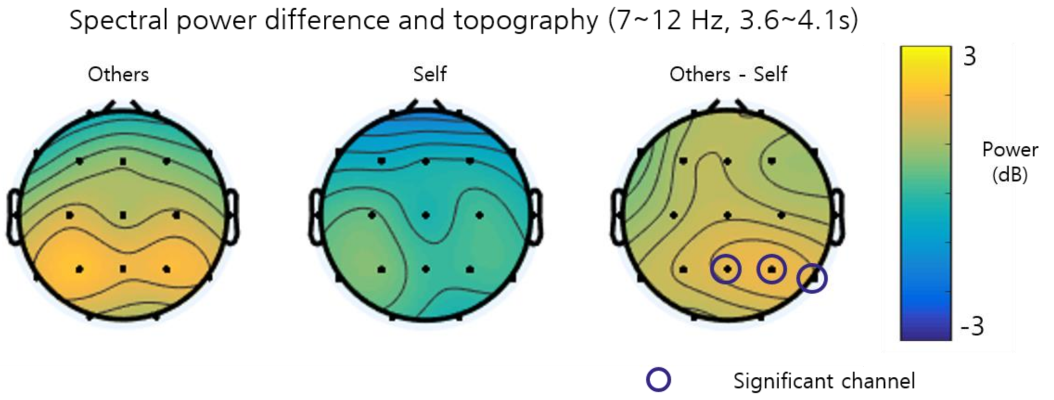

Figure 28. Topo-plot of significant time-frequency domain (left: others, middle: self, right: difference)

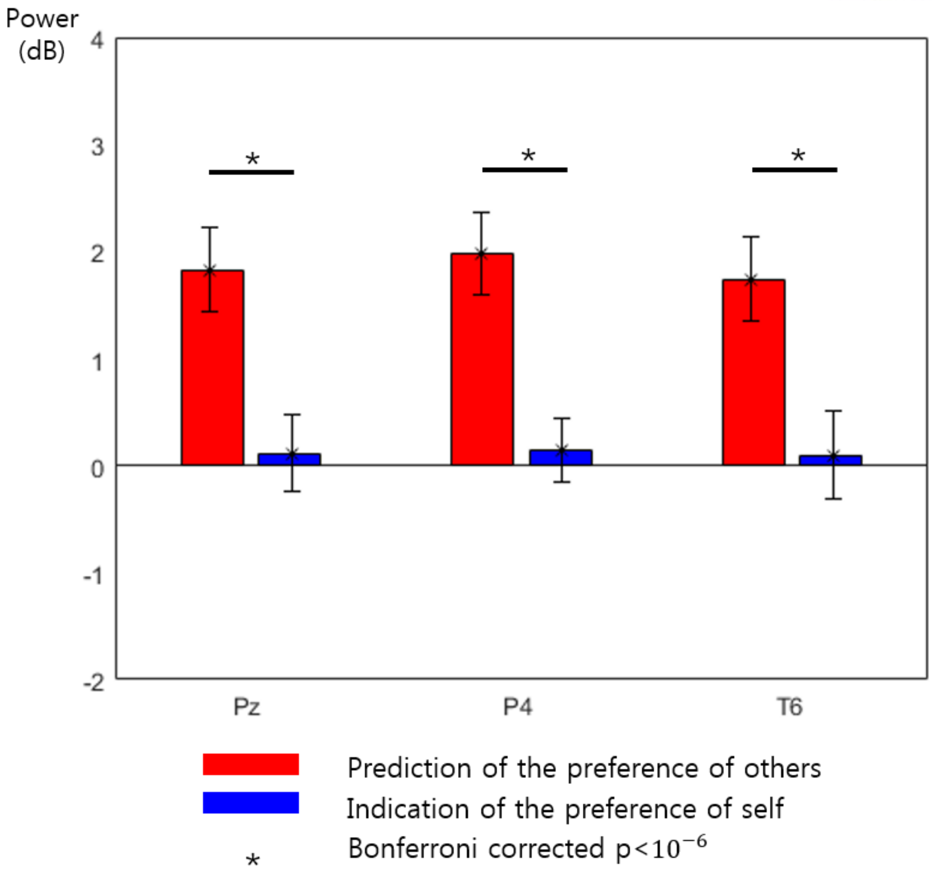

Figure 29. Bar-graph of significant time-frequency domain

2.2.3.2 Potential confounding variable

There is area of significant difference between other-trials and self-trials that do not reveal correlation with response time (r=0.07, p=0.7695) and task accuracy (r = -0.2314, p= 0.3263).

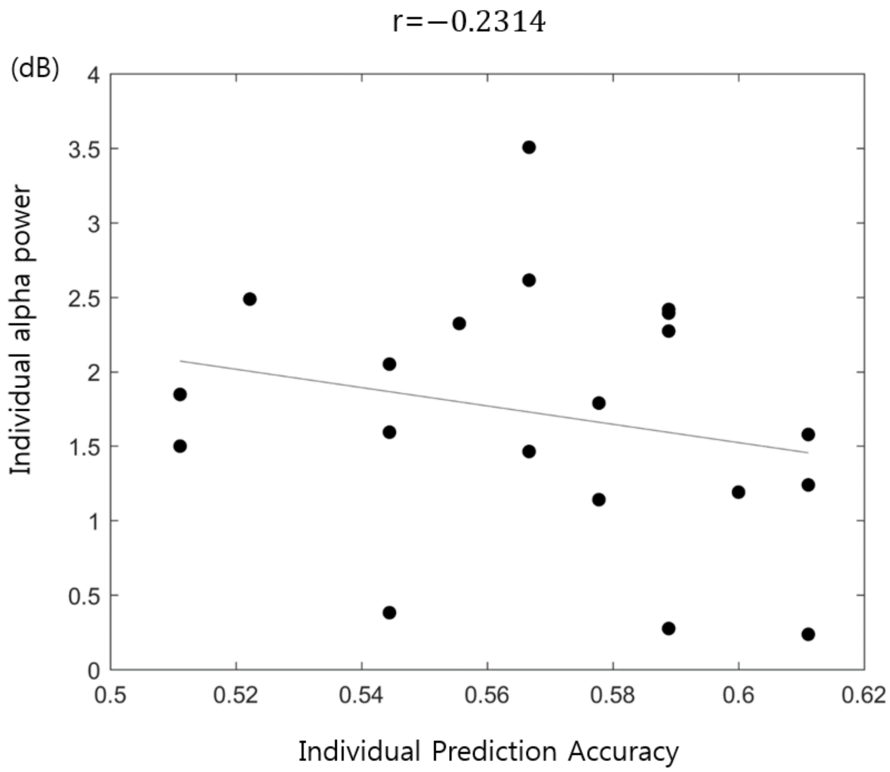

Figure 30. Correlation with individual accuracy and significant time-frequency domain activity.

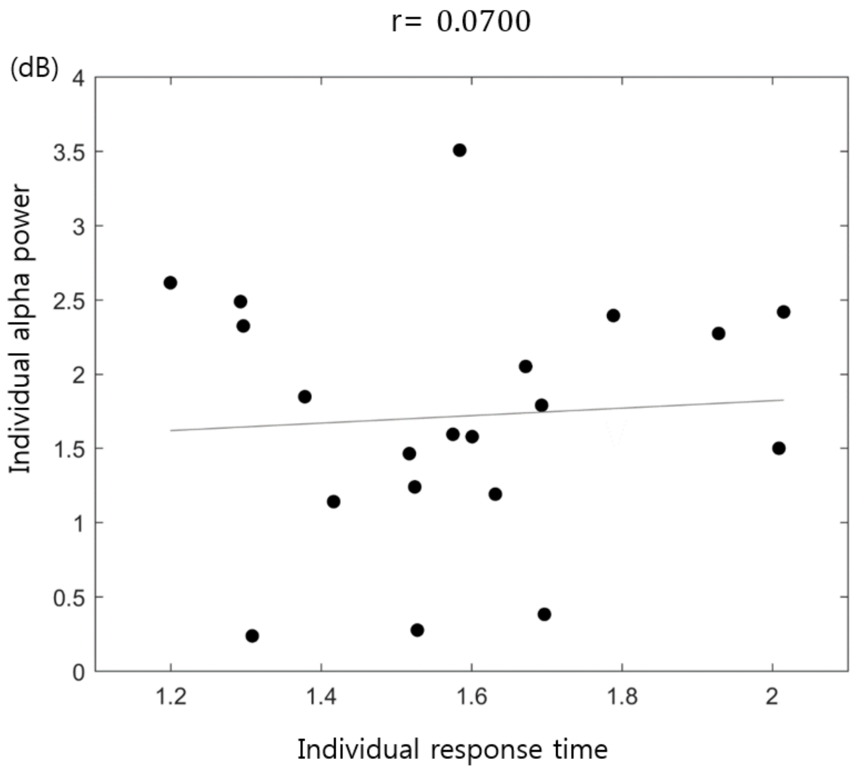

Figure 31. Correlation with response time and significant time-frequency domain activity

2.2.3.3 Correlation with other's preference estimation accuracy

We performed the correlation analysis between participants' individual prediction accuracy and spectral power of every frequency band and time window for each of the self-trials and other-trials conditions that were reported. There was no specific time-frequency combination yielding a significantly high correlation (Bonferroni corrected, $p > 0.05$). Next, we performed the correlation analysis between individual accuracy and differences of spectral power between two conditions over every combination of frequency band and time window. The two time-frequency combinations yielded significant correlations. Beta power (18 – 25 Hz) over the left temporal area (T5) in the period of 0-0.6s after item appearance was significantly correlated with individual prediction accuracy ($r = -0.8864$, Bonferroni corrected, $p < 10^{-6}$).

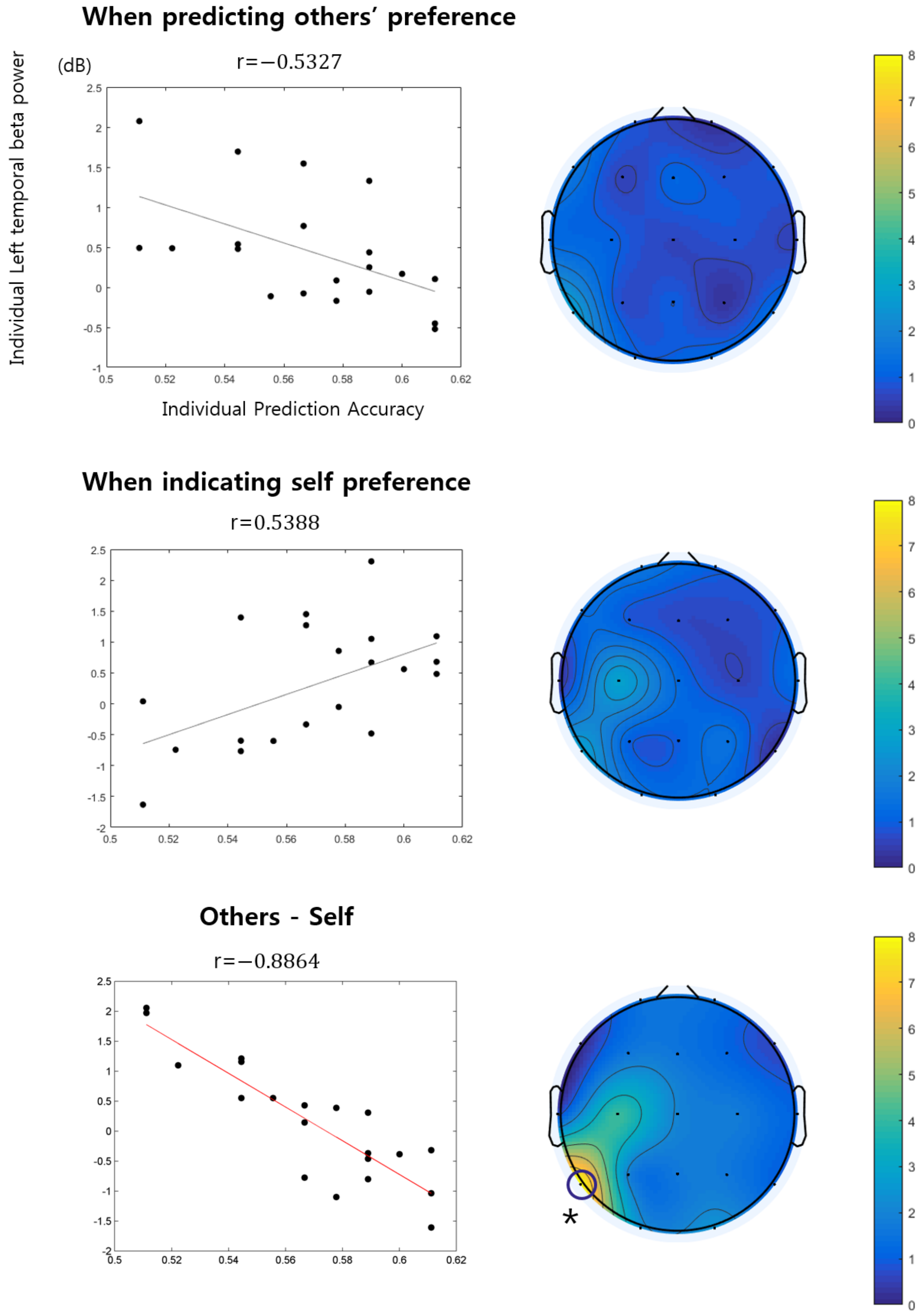

Figure 32. Correlation graph and topo-plot of significant time-frequency domain (Top: others, middle:

self, bottom: difference)

Only T5 channel of bottom shows significant correlation with individual prediction accuracy (r = -0.8864, Bonferroni corrected, p < 10-6).

2.3 Discussion

2.3.1 No difference of response time

A previous research indicated that the self-trials response time was faster than other-trials in the preference prediction experiment [41]. This study reported the opposite of our results with the difference might occurring by an experiment design. In case of a separate block of preference target like the previous research, participants can recall the target's information only one time and connect with the item's information for each of the trials. On the other hand, our design of experiment had self-trials and other-trials within one block. This difference makes the participants update the information of the target when the participants were preparing to predict the preference. For verification of this explanation, it must check the response time of sequentially same target, but this study did not have enough trials for sequential same targets. Nevertheless, the result of the response time has the explanation of the meaning of the results. As mentioned above, EEG activity showed a difference depending on the target during our experiment. When we combine these two pieces of information, it can confirm that EEG difference was not caused by the response time factor such as a workload. Furthermore, EEG activity did not correlate with the response time.

2.3.2 Difference between self-preference report and others' preference estimations

Acquiring facial information is one of the most common social activities because a face is the influential method for understanding various information such as emotions and personality traits in the social communication. [49-52] Previous studies reported that the EEG activity showed the alpha ERS when participants see the facial expression. On the contrary, Schizophrenia, which generally has less ability of recognition of social activity than healthy control, didn't show alpha ERS. [44] These incompatible two results indicate that EEG alpha ERS may reflect the social information processing when a human see facial information. In this study, an EEG activity also revealed alpha ERS when participants acquired facial information. This stage was absolutely essential for performing the preference prediction which is one of the social activities. Interestingly, however, this activity did not differ depending on the other and self-face. Consequentially, our results suggest that the EEG alpha ERS may be achieved regardless of the perspective while a human performs the process for acquiring facial information.

Our result of the EEG time-frequency analysis proposed another important point which is the significant difference of EEG activity between other-trials and self-trials during item phase in the right centroparietal region. This period, when participants performed Other-trials, also process social information using acquired facial information of others. Hence, other-trials was significantly higher than self-trials in the EEG alpha ERS. Additionally, this alpha ERS was not connected with previous alpha ERS in the face phase. The types of social activities used in two different periods are different even if the participants use the facial information. Therefore, this result suggests that the EEG alpha ERS may reflect an estimation of others' preferences, which is one of the personality traits.

2.3.3 Relationship between preference estimation accuracy and EEG oscillation

Any region of EEG oscillation didn't correlate with others' preference prediction accuracy. However, discrepancy of EEG oscillation between other-trials and self-trials revealed significant correlation with behavior performance in the left temporoparietal region. This result may be explained by behavior mechanism when participant formulate social prediction. A previous study reported that performance to predict personal traits of other people can be influenced by internal psychological processes, because the participant may use an anchoring based integrated thinking of self-state, stereotype and experience for their judgment [33]. In other words, this statement meant that other-trials has self-referential information processing and self-trials has only self-information processing. If these two kinds of information processing were formed by isolated relation, correlation with others' preference prediction accuracy should be only shown in other-trials not self-trials. However, only other-trials data analysis may not reflect the suitable self-referential information processing, because these two types of information processing is not independent. Therefore, discrepancy data of other-trials and self-trials can be one of the most potential data for reflecting self-referential information processing.

In the current study, EEG beta oscillations were used for prediction one's preference indicator about movement and musical tempo. [44-45] In addition, Northoff, G et al., suggested that self-referential information processing in the social domain was shown in MPFC, ACC, temporal pole and superior temporal sulci. Additionally, they reviewed about brain regions to describe that a medial cortex is the core system and a lateral cortex played the high-order processing. [53] Following the above statement and our second hypothesis, our result may suggest that discrepancy data of other-trials and self-trials are social self-referential information processing and it can be an indicator about estimating others' preference abilities. Moreover, item phase is more of the main phase to determine the performance of preference prediction than face phase.

2.3.4 Temporal pattern of other's preference prediction

When we arrange our results in time sequence, they appear in the order of correlation, EEG alpha oscillation and response time. Before participants judge the others' preferences, their brain perform the self-referential information processing first and social activity, which is not occurred during the report of self-preference. However, it is not all of the preference prediction process to use thin-slicing, because EEG device can only measure the cerebral cortex activity. Many previous studies also mention that frontal region such as MPFC is the crucial rule about self-referential processing. [36-38, 40, 42-43, 53] Therefore, another information processing step of thin-slicing can exist. Nevertheless, our result suggest the important one that acquiring facial information is less important than self-referential information processing for performance determination. This one support the concept feasibility of thin-slicing which does not need much time for prediction of others' traits. Additionally, the sequence of our results can be an indicator of thin-slicing process, although we don't know minimum time of information acquisition time.

2.4 Conclusion

This study demonstrated about the temporal sequence of thin-slicing process in case of others' preference predictions. When participants predict the others' preferences of movie posters, some of the participants reveal a higher accuracy than at a significant level. In EEG analysis, difference of left temporoparietal beta oscillation between self-trials and other-trials during period of connecting the information of the other persons and objects revealed significant correlation with individual accuracy. Subsequently, centroparietal alpha oscillation showed significant difference between other-trials and self-trials until the average response time. Main contribution of these results was twofold. First, the results suggest that process of connecting the information of the other person and objects is more affected to the thin-slicing accuracy than period of acquisition for the information of other persons in preference. This finding provides neural explanation evidence of thin-slicing feasibility. Second, we suggested that temporal sequence of thin-slicing in preference. Among the period of information acquisition and response, self-referential information processing exists before the social information processing. These neural evidence about thin-slicing will be helpful to understand unsolved mechanism in the psychology and neuroscience.

2.5 Limitation and Future Work

This study remains with three undisclosed phenomenon. First, experiment paradigm makes changes which the response time of self-trials and other-trials did not reveal the difference. We surmise that renewal of the target information was the main factor to arouse the difference of response time. This explanation should be accompanied by response time of sequential equal target trials, but this study did not have any sufficient amount of sequential equal trials. If the present study is added for the evidence of this verification, this evidence can help to understand the mechanism of response time and the difference according to the aspects.

Second, temporal sequence of information processing was measured in cerebral cortex only. This limitation of EEG indicate the potential stage of additional information processing because we did not know about deep brain activation. If other studies find a more accurate information flow using other methods such as connectivity analysis, thin-slicing process in preference could be more established and extended to other areas of thin-slicing.

Third, correlation with individual accuracy seems more significant when we use the difference of other-trials and self-trials. This correction phenomenon focused on the low accuracy group. (Figure. 34) This trend can be evidence of low accuracy explanation which becomes a false-consensus effect. However, it is necessary to divide a high accuracy group and a low accuracy group that utilizes a large number of participants.

These three future works will enhance to understand the process of thin-slicing.

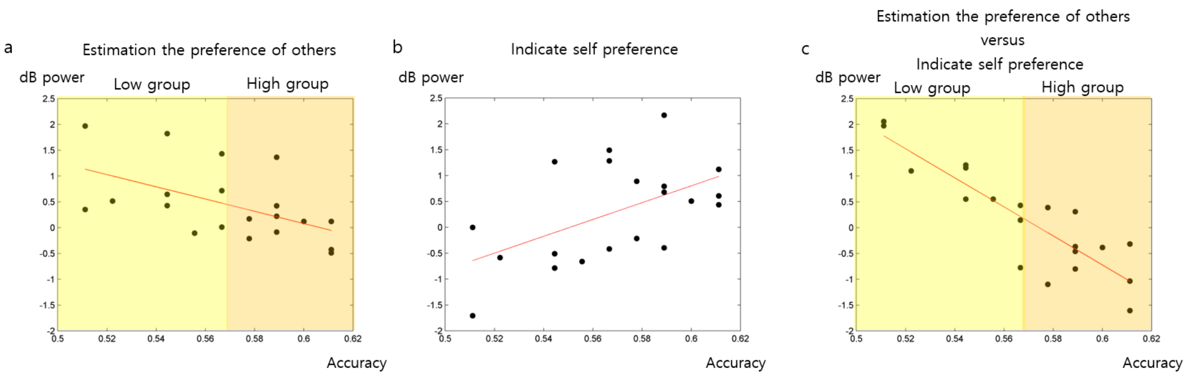

Figure 33. Correction effect of Correlation with individual accuracy.

Reference

1. Libet, J. M., & Lewinsohn, P. M. (1973). Concept of social skill with special reference to the behavior of depressed persons. *Journal of Consulting and clinical psychology*, *40*(2), 304.

2. Mundy, P., Card, J., & Fox, N. (2000). EEG correlates of the development of infant joint attention skills. *Developmental psychobiology*, *36*(4), 325.

3. Koster-Hale, J., & Saxe, R. (2013). Theory of mind: a neural prediction problem. *Neuron*, *79*(5), 836-848.

4. Premack, D., & Woodruff, G. (1978). Does the chimpanzee have a theory of mind?. *Behavioral and brain sciences*, *1*(04), 515-526.

5. Emery, N. J. (2000). The eyes have it: the neuroethology, function and evolution of social gaze. *Neuroscience & Biobehavioral Reviews*, *24*(6), 581-604.

6. Dalton, K. M., Nacewicz, B. M., Johnstone, T., Schaefer, H. S., Gernsbacher, M. A., Goldsmith, H. H & Davidson, R. J. (2005). Gaze fixation and the neural circuitry of face processing in autism. *Nature neuroscience*, *8*(4), 519.

7. Billeke, P., & Aboitiz, F. (2013). Social cognition in schizophrenia: from social stimuli processing to social engagement. *Frontiers in psychiatry*, *4*, 4.

8. Peña, M., Arias, D., & Dehaene-Lambertz, G. (2014). Gaze following is accelerated in healthy preterm infants. *Psychological science*, *25*(10), 1884-1892.

9. Von dem Hagen, E. A., Stoyanova, R. S., Rowe, J. B., Baron-Cohen, S., & Calder, A. J. (2014). Direct gaze elicits atypical activation of the theory-of-mind network in autism spectrum conditions. *Cerebral cortex*, *24*(6), 1485-1492.

10. Soto-Icaza, P., Aboitiz, F., & Billeke, P. (2015). Development of social skills in children: neural and behavioral evidence for the elaboration of cognitive models. *Frontiers in neuroscience*, *9*, 333.

11. Meyer-Lindenberg, A. (2010). From maps to mechanisms through neuroimaging of schizophrenia. *Nature*, *468*(7321), 194.

12. Gladwell, M. (2007). *Blink: The power of thinking without thinking*. Back Bay Books.

13. Albright, L., Kenny, D. A., & Malloy, T. E. (1988). Consensus in personality judgments at zero acquaintance. *Journal of personality and social psychology*, *55*(3), 387.

14. Funder, D. C., & Colvin, C. R. (1988). Friends and strangers: acquaintanceship, agreement, and the accuracy of personality judgment. *Journal of personality and social psychology*, *55*(1), 149.

15. Watson, D. (1989). Strangers' ratings of the five robust personality factors: Evidence of a surprising convergence with self-report. *Journal of Personality and Social Psychology*, *57*(1), 120.

16. Engell, A. D., Haxby, J. V., & Todorov, A. (2007). Implicit trustworthiness decisions: automatic coding of face properties in the human amygdala. *Journal of cognitive neuroscience*, *19*(9), 1508-1519.

17. Van't Wout, M., & Sanfey, A. G. (2008). Friend or foe: The effect of implicit trustworthiness judgments in social decision-making. *Cognition*, *108*(3), 796-803.

18. Stillman, T. F., Maner, J. K., & Baumeister, R. F. (2010). A thin slice of violence: Distinguishing violent from nonviolent sex offenders at a glance. *Evolution and Human Behavior*, *31*(4), 298-303.

19. Johnson, K. L., Gill, S., Reichman, V., & Tassinary, L. G. (2007). Swagger, sway, and sexuality: Judging sexual orientation from body motion and morphology. *Journal of personality and social psychology*, *93*(3), 321.

20. Fetchenhauer, D., Groothuis, T., & Pradel, J. (2010). Not only states but traits—Humans can identify permanent altruistic dispositions in 20 s. *Evolution and Human Behavior*, *31*(2), 80-86.

21. McArthur, L. Z., & Baron, R. M. (1983). Toward an ecological theory of social perception. *Psychological review*, *90*(3), 215.

22. Banaji, M. R., Hardin, C., & Rothman, A. J. (1993). Implicit stereotyping in person judgment. *Journal of personality and Social Psychology*, *65*(2), 272.

23. Snyder, M., Tanke, E. D., & Berscheid, E. (1977). Social perception and interpersonal behavior: On the self-fulfilling nature of social stereotypes. *Journal of Personality and Social Psychology*, *35*(9), 656.

24. Gilbert, D. T., & Krull, D. S. (1988). Seeing less and knowing more: The benefits of perceptual

ignorance. *Journal of Personality and Social Psychology*, *54*(2), 193.

25. Hall, J. A. (1978). Gender effects in decoding nonverbal cues. *Psychological bulletin*, *85*(4), 845.

26. Ambady, N., & Rosenthal, R. (1992). Thin slices of expressive behavior as predictors of interpersonal consequences: A meta-analysis. *Psychological bulletin*, *111*(2), 256.

27. Albrechtsen, J. S., Meissner, C. A., & Susa, K. J. (2009). Can intuition improve deception detection performance? *Journal of Experimental Social Psychology*, *45*(4), 1052-1055.

28. Kang, P., Lee, J., Sul, S., & Kim, H. (2013). Dorsomedial prefrontal cortex activity predicts the accuracy in estimating others' preferences. *Frontiers in human neuroscience*, *7*

29. North, M. S., Todorov, A., & Osherson, D. N. (2010). Inferring the preferences of others from spontaneous, low-emotional facial expressions. *Journal of Experimental Social Psychology*, *46*(6), 1109-1113.

30. West, P. M. (1996). Predicting preferences: An examination of agent learning. *Journal of Consumer Research*, *23*(1), 68-80.

31. Hoch, S. J. (1988). Who do we know: Predicting the interests and opinions of the American consumer. *Journal of Consumer Research*, *15*(3), 315-324.

32. Frith, U., & Frith, C. D. (2003). Development and neurophysiology of mentalizing. *Philosophical Transactions of the Royal Society of London B: Biological Sciences*, *358*(1431), 459-473.

33. Hoch, S. J. (1987). Perceived consensus and predictive accuracy: The pros and cons of projection. *Journal of Personality and Social Psychology*, *53*(2), 221.

34. Kurt, D., & Inman, J. J. (2013). Mispredicting others' valuations: Self-other difference in the context of endowment. *Journal of Consumer Research*, *40*(1), 78-89.

35. Kampe, K. K., Frith, C. D., & Frith, U. (2003). "Hey John": signals conveying communicative intention toward the self activate brain regions associated with "mentalizing," regardless of modality. *The Journal of neuroscience*, *23*(12), 5258-5263.

36. Platek, S. M., Keenan, J. P., Gallup, G. G., & Mohamed, F. B. (2004). Where am I? The neurological correlates of self and other. *Cognitive Brain Research*, *19*(2), 114-122.

37. Frith, C. D., & Frith, U. (1999). Interacting minds--a biological basis. *Science*, *286*(5445), 1692-1695.

38. Vogeley, K., Bussfeld, P., Newen, A., Herrmann, S., Happé, F., Falkai, P., ... & Zilles, K. (2001). Mind reading: neural mechanisms of theory of mind and self-perspective. *Neuroimage*, *14*(1), 170-181.

39. Cook, J. L. (2014). Task-relevance dependent gradients in medial prefrontal and temporoparietal cortices suggest solutions to paradoxes concerning self/other control. *Neuroscience & Biobehavioral Reviews*, *42*, 298-302.

40. Jimura, K., Konishi, S., Asari, T., & Miyashita, Y. (2010). Temporal pole activity during understanding other persons' mental states correlates with neuroticism trait. *Brain research*, *1328*, 104-112.

41. Seger, C. A., Stone, M., & Keenan, J. P. (2004). Cortical activations during judgments about the self and an other person. *Neuropsychologia*, *42*(9), 1168-1177.

42. Johnson, S. C., Schmitz, T. W., Kawahara-Baccus, T. N., Rowley, H. A., Alexander, A. L., Lee, J., & Davidson, R. J. (2005). The cerebral response during subjective choice with and without self-reference. *Journal of cognitive neuroscience*, *17*(12), 1897-1906.

43. Jung, D., Sul, S., & Kim, H. (2013). Dissociable neural processes underlying risky decisions for self versus other.

44. Popova, P., Popov, T. G., Wienbruch, C., Carolus, A. M., Miller, G. A., & Rockstroh, B. S. (2014). Changing facial affect recognition in schizophrenia: Effects of training on brain dynamics. *NeuroImage: Clinical*, *6*, 156-165.

45. Kang, J. H., Kim, S. J., Cho, Y. S., & Kim, S. P. (2015). Modulation of alpha oscillations in the human EEG with facial preference. *PloS one*, *10*(9), e0138153.

46. Bauer, A. K. R., Kreutz, G., & Herrmann, C. S. (2015). Individual musical tempo preference correlates with EEG beta rhythm. *Psychophysiology*, *52*(4), 600-604.

47. Boksem, M. A., & Smidts, A. (2015). Brain responses to movie trailers predict individual preferences for movies and their population-wide commercial success. *Journal of Marketing Research*, *52*(4), 482-492.

48. Klem, G. H., Lüders, H. O., Jasper, H. H., & Elger, C. (1999). The ten-twenty electrode system of the International Federation. *Electroencephalogr Clin Neurophysiol*, *52*(3), 3-6.

49. Jack, R. E., & Schyns, P. G. (2015). The human face as a dynamic tool for social communication. *Current Biology*, *25*(14), R621-R634.

50. Willis, J., & Todorov, A. (2006). First impressions making up your mind after a 100-ms exposure to a face. *Psychological science*, *17*(7), 592-598.

51. Berry, D. S., & McArthur, L. Z. (1985). Some components and consequences of a babyface. *Journal of personality and social psychology*, *48*(2), 312.

52. Ekman, P. (1993). Facial expression and emotion. *American psychologist*, *48*(4), 384.

53. Northoff, G., Heinzel, A., De Greck, M., Bermpohl, F., Dobrowolny, H., & Panksepp, J. (2006). Self-referential processing in our brain—a meta-analysis of imaging studies on the self. *Neuroimage*, *31*(1), 440-457.